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GBCSA Energy and Water Benchmark Methodology - Final Report

Prepared for: GBCSA (via Aurecon)
Prepared by: Exergy: Dr. Paul Bannister; Haibo Chen
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Author	Haibo Chen
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EXECUTIVE SUMMARY

This report presents the development and details of performance based benchmarks for South African office buildings. The approach adopted is consistent with similar international tools developed to benchmark operational energy performance. The report is in its draft format and will be finalised once the benchmark methodology has been reviewed and approved.

A large sample of office buildings located throughout South Africa has been gathered as a part of the project and this data has been used as an empirical basis for the energy and water benchmark models. Due to the limitations on available metering data, the South African data set is limited to the analysis of whole building energy and water consumption. As preliminary analysis, a number of demographic factors and their impact on building EUI were examined; it was demonstrated that variations in sample building EUI and WUI were largely unrelated to factors such as building location, building size, year of construction/refurbishment, % of active cooling coverage, irrigation and inclusion of energy intensive end uses.

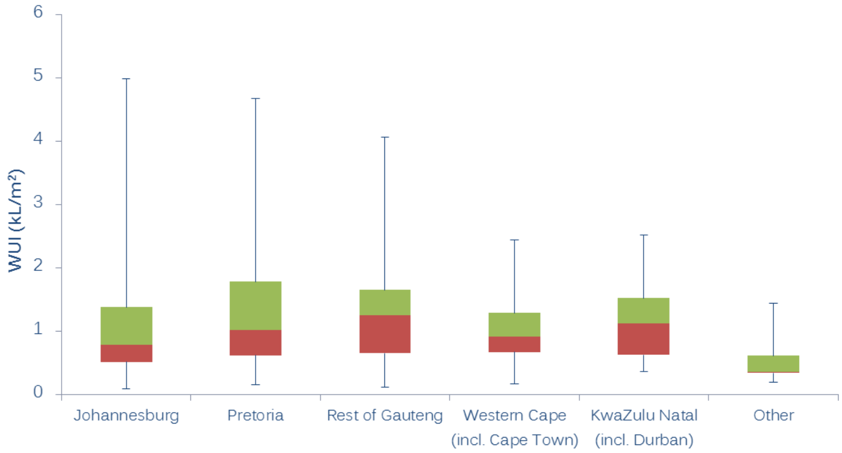
From a benchmarking perspective, building size (Gross Lettable Area) was the most significant consumption driver for both energy and water benchmarks. However, additional empirical and theoretical corrections have been made to account for various building and location specific characteristics that are understood to have an impact on energy/water consumption. The key constituents of the energy benchmark model are building size, computer density, climate and occupancy hours; the latter two are theoretical corrections based on simulation outcomes in IES. Meanwhile, the key constituents of the water benchmark model are building size, occupant density, climate and occupancy hours. A theoretical water climate correction has been adopted in the water benchmark while a theoretical correction was derived for occupancy hours is comparable to the simulated occupancy-hours correction for energy.

This report also details the derivation of recommended rating bands for both the energy and water rating tools based on the benchmark model; the rating system recommended incorporates a 10 point rating scale that is based on the relative performance of buildings with respect to their peers under the relevant benchmarks.

Contents

GLOSSARY

Box whisker plot: the box-whisker plot is ideal for presenting differences between subsets of data. Within each set, the boxes represent the 25th to 75th percentiles of data by size while the ends of the whiskers extend to the maximum and minimum values within that population. The two halves of the boxes meet at the observed median.



Cooling Degree Days (CDD): A degree day represents the proportion of a day where the outside air conditions require a certain level of cooling to reach the desired base temperature level. The formula is used for each segment of time for which the temperature is known:

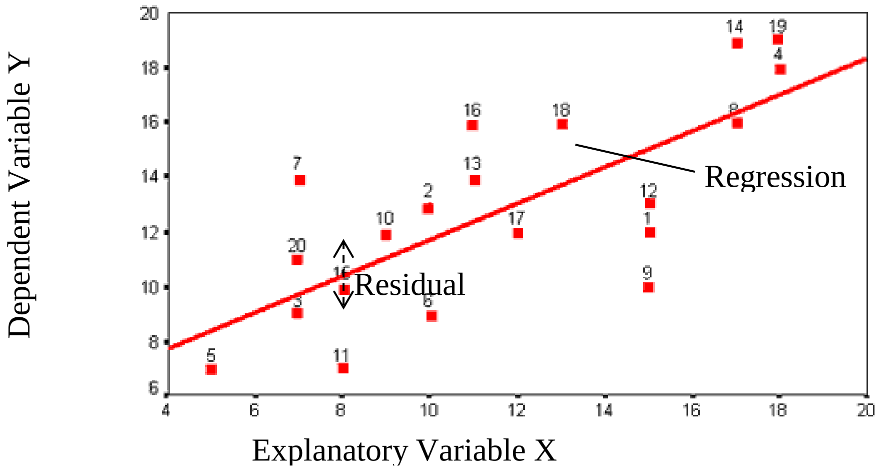
[(OA temp) - (base temp)] × (proportion of the day)

The sum of these weighted values for a whole day gives the number of cooling degree days, for that base, for that day.

For example, 2 hours at 16°C represents (16-15)*2*1/24 of a Cooling Degree day with base 15°C.

Correlation Coefficient (R^2): is a measure of the correlation strength between two sets of data. The coefficient varies between -1 and +1 with -1 indicating a purely negative correlation (one set of data is the exact negative proportion of the other set) and +1 indicating a purely positive correlation. The weaker the relationship is between the two sets of data, the closer the coefficient will be to zero.

Least Squares Regression: part of regression modelling is finding the linear model which "best fit" the data. The method of least squares assumes that the best model is obtained when the sum of squared errors between the predicted Y value and the actual measured Y value is minimised. Graphically (see below), the regression error (residual) is the distance between the actual data (data point) and the regression line (fitted model). The least squares approach minimises the sum of all squared errors to produce the line of "best fit".



Linear Regression: is an approach to modelling the relationship between a dependent variable Y and one or more explanatory variables X. The relationship is assumed to be linear in nature and takes the form $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i$, where $\beta_{0\ldots i}$ are scalar constants (referred to as coefficients if they are associated with a particular X variable) and $X_{1\ldots i}$ are the explanatory variables. The scalar constants are most often evaluated using least squares regression (minimising sum of squared errors).

Mean: the mean is otherwise known as the unweighted arithmetic mean and is the average value for a given finite set of observations/values. In the context of the project, the mean is also synonymous with the expected value of a given observation.

Median: In the context of data analysis, the median is explicitly the middle value of a finite set of observations/values which can be found by arranging all the observations from lowest value to highest value and selecting the middle one. If there is an even number of observations, then the median is the mean of the two most middle values.

NABERS: the National Australian Built Environment Rating System (NABERS) is a performance-based rating system for existing buildings. NABERS rates a building on the basis of its measured operational impacts on the environment, and provides a simple indication of how well a building is managing these environmental impacts compared with its peers and neighbours. There are several variants of NABERS that are used to rate different building types, namely: Offices, Hotels, Hospitals, Shopping Centres and Data Centres.

p-value: the p-value is a measure for the significance of a regression variable. As part of the regression output, it represents the probability that the regression coefficient for the variable in question is actually 0 (insignificant in a regression model). Ideally, the p-value is to be as close to 0 as possible to ensure coefficient/variable significance. As part of a t-test, the p-value is the probability that the null hypothesis is true; the null hypothesis is usually rejected if the p-value is lower than 0.05 (less than 5% chance the null hypothesis is true).

Residuals: in mathematical terms, the regression model for elevator consumption can be generalised into the following form:

$$Y = \hat{Y} + \varepsilon$$

Where Y denotes the actual reported consumption, $\hat{Y}$ denotes the regression predicted consumption and the remaining unexplained variation (residual) is denoted ε. Residual analysis plays an important role in determining the validity of the regression model. If ε is found to have a significant relationship with any variable(s), then the model predicted $\hat{Y}$ is incomplete as a good regression model should only present random noise in ε.

1 Introduction

In recent years, awareness of commercial building energy efficiency has increased substantially worldwide. In order to further increase awareness and reduce energy consumption and carbon emissions, a number of building energy efficiency rating tools have been developed to compare and rate office building environmental performance. Rating tools such as NABERS, Energy Star, LEED, BREEAM and Green Star have adopted significantly different methodologies to benchmark office building energy efficiency with varying degrees of success and industry uptake.

In a bid to encourage efficient office building operations, the South Africa Green Building Council is developing a new performance based rating tool for whole building energy and water consumption in commercial (office) buildings. This study has collected substantial real world data on office building energy consumption and used it as an empirical basis for the development of a performance based rating tool. The study is being conducted in collaboration with Aurecon South Africa who provided much of the raw data analysed and presented throughout this report.

The intent of this document is to:

- Present all data collected as part of the study.
- Present the logical steps, assumptions made and methodology used to derive the benchmark model.
- Present the coefficients and mechanics of the benchmark model.

1.1 Performance Based Benchmarks

It is important to review how a performance based benchmark operates. There are essentially two types of efficiency rating tools available: design based and performance based. In design based tools, facilities are rewarded for features or designs that are thought to be efficient. On the other hand, performance based tools focus on comparing metrics such as measured energy consumption and productive output; facilities are deemed more efficient if they consume less energy/water for a given level of productive output. The benchmark presented in this report is a purely performance based tool that benchmarks energy and water consumption against population median performance levels to assess the building's relative environmental impact when compared to its peers.

For illustrative purposes, consider an office building that has reduced its energy consumption. Under a performance based benchmark tool, if the productive output of the building remains the same but the energy consumption decreases, the building is said to have increased its energy efficiency. On the other hand, if the reduction in energy use is matched by an equal level of reduction in productive output (e.g. less occupied area), then the building has not improved its energy efficiency (the energy reduction is merely a flow-on effect from having to service fewer occupants). By identifying the underlying relationship between resource input and productive output, the benchmark tool can directly assess office buildings of different productive output levels (e.g. size, operating hours etc.).

While performance based benchmarks may be used to encourage efficient practices, the benchmarks themselves do not take design/implemented solutions directly into consideration; only the impacts of these solutions are considered. In this manner, a performance based benchmark encourages innovation in the achievement of energy and water efficiency rather than the prescriptive approach adopted by design-based assessment systems that may hinder innovation and in some cases may even produce perverse outcomes.

1.2 Building Energy Split

As identified in the early stages of the project, the base building (landlord)/tenant metering split that is present in Australia (and New Zealand and Hong Kong) is largely absent from most major economies (including the US, UK and mainland Europe). The data collected to date confirm that office buildings in South Africa also lack such metering splits and this will limit the type of benchmarks available. Where NABERS in Australia was able to develop separate benchmarks for base building, tenant and whole building, the extent of the energy data available for South Africa limits the energy benchmark model to whole building only.

1.3 Alternative fuel sources

While the data collected to date include substantial information on building characteristics and whole building energy and water use, no information has been collected on alternative fuel sources such as natural gas and diesel since their use in South African office buildings is limited. In light of such gaps in information, several important caveats must be observed when interpreting the data collected:

- The ability to correlate energy use to climate data is limited as electricity is used solely to provide both space cooling and space heating. It should be expected that correlations to energy use will not be significant for the range of climate zones as cooler zones will see higher heating energy while warmer zones will see higher cooling energy.
- The outcomes of the benchmark and the relative position of buildings may be erroneous, especially for buildings where natural gas or fuel consumption is significant. However, such buildings are understood to be rare in SA.

1.4 Statistical methods

1.4.1 Linear regression

Linear regression was used extensively throughout the project to quantify (and sometimes justify) the inclusion of various consumption drivers in the benchmark model. Regression modelling uses mathematical equation(s) to estimate the underlying relationship between a dependent variable (in our case the office building energy consumption) and one or more explanatory variables (for this project the consumption drivers for office buildings). The aim of multiple linear regression in the context of the GBCSA benchmarking is to establish a statistically significant linear relationship between office building energy consumption and the potential consumption drivers. The relationship observes a linear form, i.e.

$$Predicted\ Consumption = \beta_0 + \beta_1 Factor1 + \beta_2 Factor2 + \beta_3 Factor3 + \cdots$$

Where Factor1, Factor2, Factor3… are consumption drivers that affect power consumption and are scalar constants that reflect the impact of each driver respectively.

The values of the constants are determined through a method called the “least squares fit” where the constants β (impact) for each variable are optimized through the minimization of errors. Multiple linear regression provides a useful tool to examine the applicability and validity of various consumption drivers and much of the preliminary analysis was based on this methodology.

1.4.2 T-tests

In addition to regression modelling, Statistical t-tests have been used throughout to test for significance of observed differences between data sets. More specifically, the t-test (or student's t-test) is a statistical test used to compare the means of two samples and check whether they are significantly different. Usually, the null hypothesis assumes that the two samples have equal means; the t-test then estimates the statistical probability that the null hypothesis is true. The null hypothesis is usually rejected (means are significantly different) when this probability is less than 0.05 (5% chance). The t-test assumes:

- A normal distribution for both samples being tested
- Equal variance between the two samples (which can be confirm with F-test)

Where the sample variances are unequal, the Welch's t-test can be carried out (which is only a slightly modified version of the student's t-test).

The two main types of t-tests are:

- Unpaired t-test – the samples are independent of each other
- Paired t-test – for instances where the two samples are strictly related to each other in some direct way, e.g. before and after measurements.

This study deals exclusively with independent data sets so the unpaired t-test has been used throughout.

There are both one-tailed and two-tailed t-tests. In a two-tailed test, the null hypothesis is rejected when the mean of one sample is either sufficiently larger or smaller than the other sample mean. In a one-tailed test, the alternative hypothesis (rejection criterion for the null hypothesis) is preselected and limited to one of the rejection criteria (larger or smaller). Usually a two tailed test is used as it is a stricter test for difference (covers both scenarios).

2 Sample Data

2.1 Data Collection Process

Data for the benchmark tool was gathered via voluntary questionnaires distributed to building/portfolio managers in both the public and private sectors by Aurecon South Africa.

The intent of the survey was to collect a representative sample of South African office buildings upon which to base the analysis. Critical to this was the achievement of a suitable coverage and diversity of the distinguishing parameters for office buildings. In particular, it was critical to achieve a suitable distribution across:

- Building size
- Building quality
- Geographic location
- Building efficiency (measured by Energy Use Intensity kWh/m^2/year or Water Use Intensity kL/m^2/year)

The survey forms requested a broad range of information relating to office building characteristics to help determine the empirical relationships between potential consumption drivers and energy/water consumption.

2.2 Data Subsets

The data collected fall into one of two subsets based on the level of information provided.

- **Basic** – this subset includes buildings that were only able to provide information on postcode, building size (gross lettable area) and consumption data (kWh and kL). While the basic subset is of limited use in benchmarking, it is useful in determining data coverage (particularly with respect to demographics and sample representativeness).
- **Detailed** – this subset includes buildings that provided a response to the full questionnaire template including detailed information on many physical/operational attributes, energy coverage and data quality. The detailed subset can be used to infer population characteristics and is the basis of the technical benchmark development.

Analysis of the combined sample is critical in assessing whether the collected sample is representative of the office building population in South Africa. The sizes of the basic and detailed subsets also vary depending on the benchmark (energy or water).

2.3 Data Summary

2.3.1 Filtering and QA of Sample Data

In total, energy and water data for 344 buildings was collected. However, in order to obtain a fair and representative benchmark model, it is essential that the characteristics and consumption data underlying any analysis is accurate and comparable to other buildings within the market. For this reason, sites with considerable gaps in consumption data or obviously spurious energy/water intensities were filtered out of the final sample data set; more specifically, a site was excluded if:

- Annual consumption included more than 3 months of estimated data; or
- whole building Energy Use Intensity (EUI) was less than 80 kWh/m^2/year or greater than 900 kWh/m^2/year; or
- whole building Water Use Intensity (WUI) was less than 0.1 kL/m^2/year or greater than 5 kL/m^2/year; or
- the site did not specify the metering period for the consumption data reported.

Table 1 below present the number of sites included and excluded in the study following the initial QA.

	Basic	Detailed	Combined	No. of sites excluded
Energy	155	87	242	102
Water	172	84	256	88

Table 1: Number of useful data responses by subsets

2.3.2 Energy Data Coverage

The energy sample data set was assessed for coverage over the full range of:

- Geographic location (region and major urban centres)
- Building size
- Energy Use Intensity

Ideally, building quality should also be separately assessed to ensure that the sample is not biased towards particular building quality grade; however, since there is no formal measure of building quality in South Africa, the assumption has been made that building size correlates strongly with building quality (and this is certainly the case in Australia).

Geographic Location

Distribution of the building responses by geographic region is shown in Table 2 below.

Region	GLA (m^2)	No. of Buildings	kWh/year
Johannesburg	1,233,695	96	300,829,736
Pretoria	627,582	56	140,948,632
Rest of Gauteng	448,815	14	136,483,566
Western Cape (incl. Cape Town)	442,513	42	104,616,327
KwaZulu Natal (incl. Durban)	265,187	25	55,365,778
Other	63,808	9	12,996,031
Total	**3,081,600**	**242**	**751,240,069**

Table 2: Distribution of sample data (energy) by geographic region

The geographic distribution of buildings is presented graphically in Figure 1.

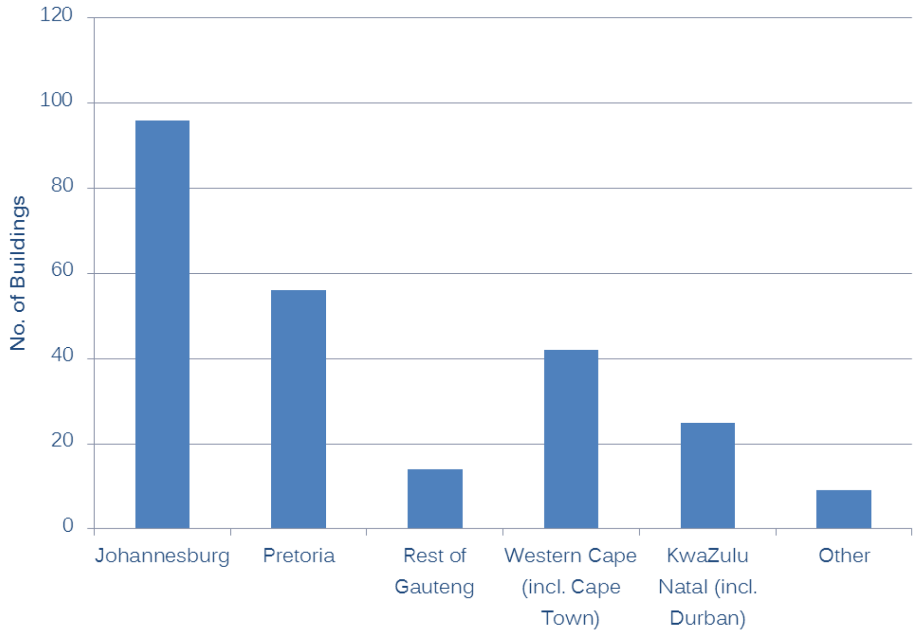


Figure 1: Geographic distribution of sample data (energy)

Achieving a suitable distribution across geographic locations is important as location is often correlated to socioeconomic/demographic/climatic characteristics which are not easily measured. For example, major urban centres experience different climates due to their geographical locations. The concentration of respondents to the major urban centres (e.g. Johannesburg and Pretoria) is expected as this reflects the nature of the commercial building stock in South Africa. The important point to draw from Figure 1 is that all major urban centres (including Cape Town and Durban) appear well represented in the sample data set.

As Table 2 indicates, the energy sample data covers over 3 million square metres of office building gross lettable area in a total of 242 buildings. The total annual energy footprint of these buildings was over 751 GWh per year. To verify coverage of the collected sample, data presented in Table 2 can be compared to the market aggregate information from the Investment Property Database (IPD) which covers more than 60% of the SA property market by asset value (total of 683 buildings).

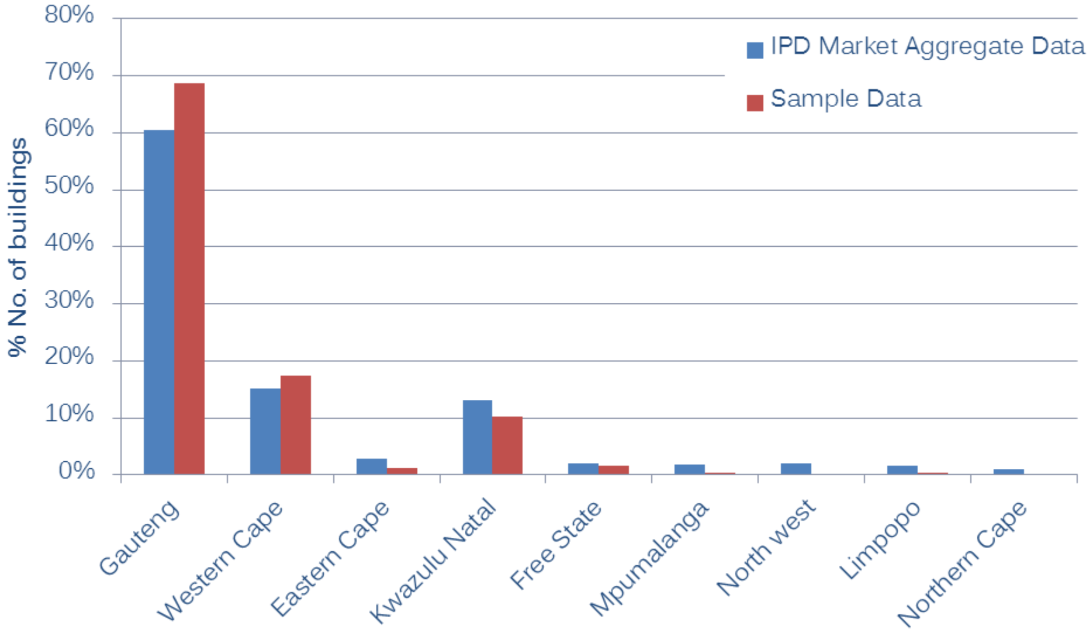


Figure 2: Comparison of IPD market data and sample data coverage by no. of buildings

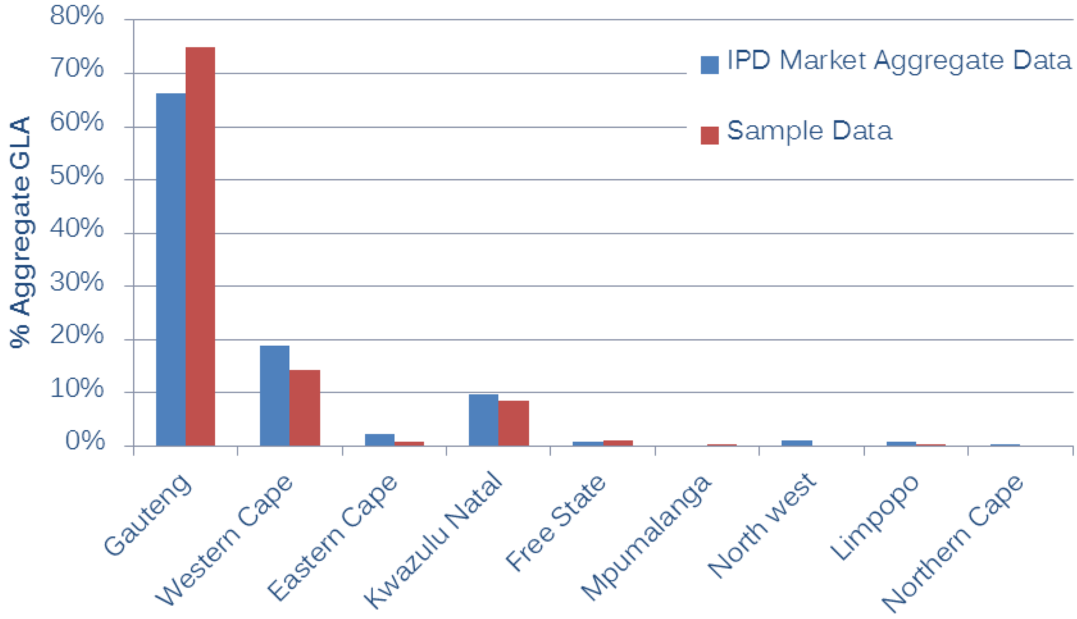


Figure 3: Comparison of IPD aggregate market data and sample data coverage by GLA

Figure 2 and Figure 3 demonstrate that a suitable sample has been obtained for the purposes of this study. The distributions of sample buildings almost exactly reflect the aggregate market data provided by IPD. There is therefore a strong basis to believe that the full sample is a comprehensive and representative sample of the overall office building population in SA.

Building Size

Building size is a key variable in the benchmarking methodology as it is one of the few metrics that can be measured and validated for any given building. Also, building size is likely to correlate strongly with other factors such as number of occupants. For these reasons, it is important that office buildings of all sizes are adequately represented to ensure that the benchmark is developed without bias for size.

The sample data has been categorised into 6 bins of building sizes, the descriptive statistics for these size ranges are presented in Table 3 below.

GLA Category	No. of buildings	% of Total	GLA (m^2)	% of sample GLA	kWh/year	Average EUI kWh/m^2	Median EUI kWh/m^2
0-2,000 m^2	22	9%	26,694	1%	5,052,233	187	198
2,001-5,000 m^2	64	26%	224,593	7%	46,846,231	208	206
5,001 - 10,000 m^2	57	24%	413,446	13%	91,098,892	216	203
10,001 - 20,000 m^2	60	25%	812,773	26%	184,271,947	223	203
20,001 - 30,0000 m^2	21	9%	495,591	16%	124,415,775	251	203
>30,000 m^2	18	7%	1,108,503	36%	299,554,991	255	206
Total	**242**	**100%**	**3,081,600**	**100%**	**751,240,069**	**223**	**205**

Table 3: Distribution of sample data (energy) by building size category

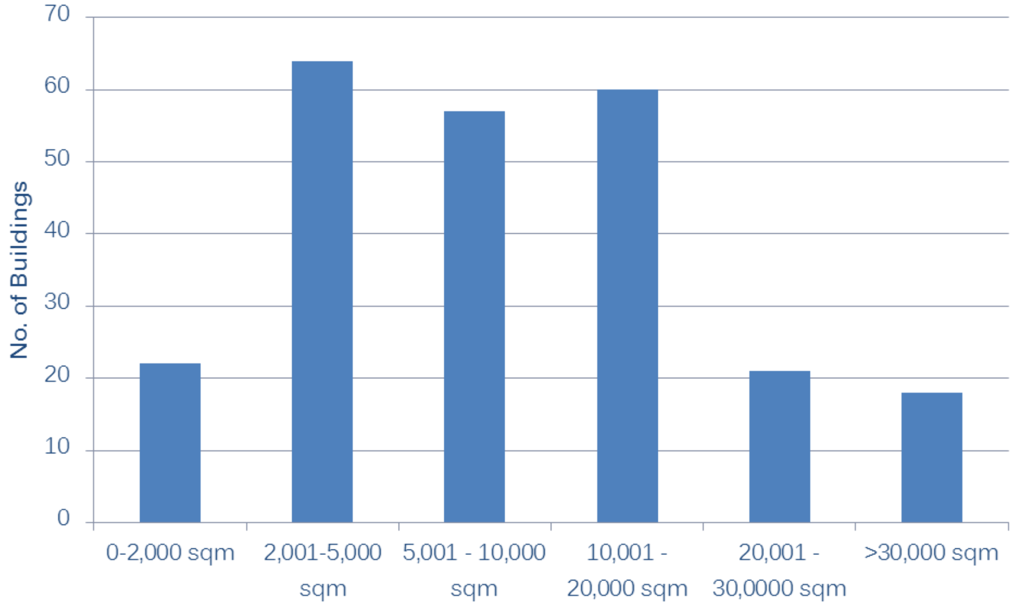


Figure 4: Sample building size distribution by number of buildings (Energy)

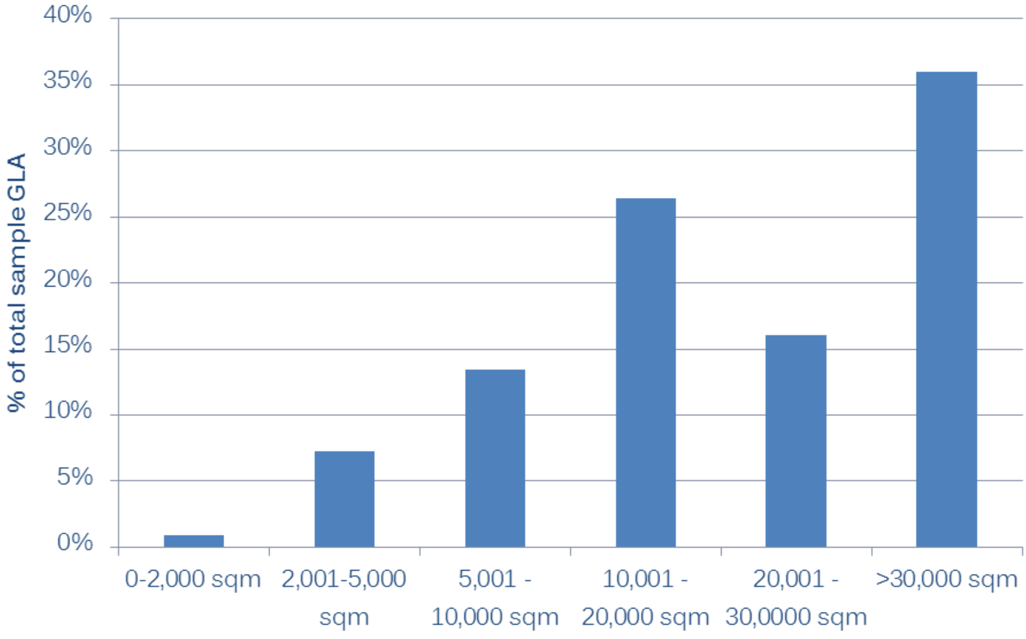


Figure 5: Sample building size distribution by % of total sample GLA (Energy)

Ideally, more data on the smallest office buildings (0-2000 m^2 GLA) would improve size coverage. Indeed, other performance based rating tools have historically struggled to obtain market information and drive market transformations in this sector. From a policy perspective, the limited data on smaller office buildings may lead to perverse benchmark outcomes for the smaller properties below the 2000 m^2 threshold. All other building sizes appear well represented in the data set.

Energy Use Intensity (EUI)

Energy use intensity (EUI) is a metric that many ratings tools and international studies use to compare building energy efficiency. The EUI is defined as

$$EUI\ (kWh/m^2)\ =\ \frac{Annual\ Energy\ Consumption\ (kWh)}{Building\ Area\ (m^2)}$$

The definition of the terms above vary by application and source but in the context of this report, annual energy consumption is the whole building annual electricity consumption in kWh while the building area is the gross lettable area of the whole building in m^2.

As the EUI is a commonly quoted figure, there is a good deal of existing data on EUI distributions of commercial building stocks globally. In one of the recent research studies conducted by the University of Cambridge (Choudhary 2011), the EUI distribution for a large sample (436 buildings) of UK London public sector office buildings was published. This provides us with an opportunity to verify the sample EUI distribution.

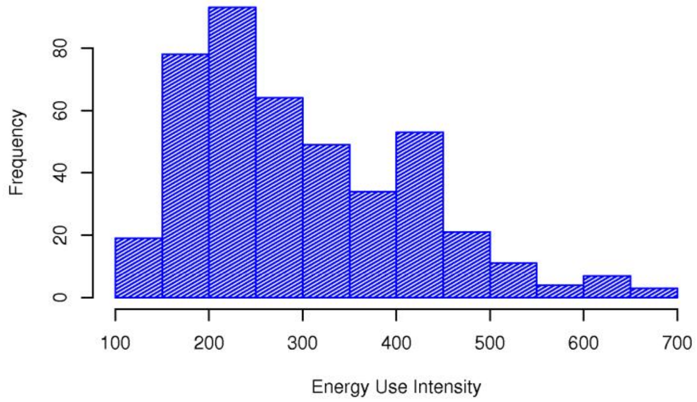


Figure 6: EUI distribution of London public sector office building sample

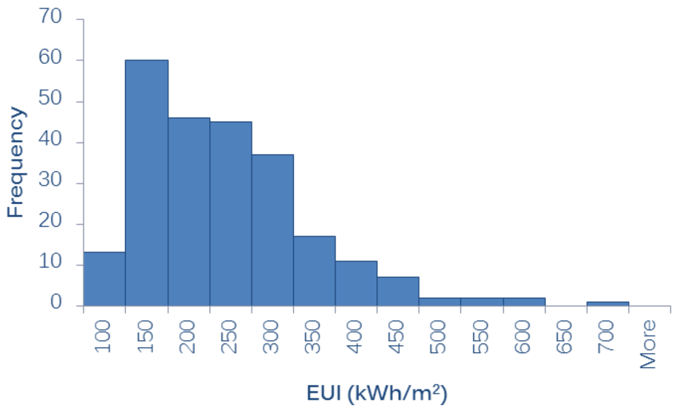


Figure 7: EUI distribution of South Africa office building sample

Based on the similarity in EUI distributions found in Figure 6 (London, UK) and Figure 7 (South Africa), an important inference may be made: the current working data set appears sufficiently large as sampling bias is not evident (the results do not warrant a larger sample to be collected). Figure 7 also suggests that there is adequate representation for the full range of EUI; the rating tool will therefore be able to define a desirable distribution for the spectrum of expected rating outcomes.

It is also noted that the EUI data gathered for this project are broadly compatible with the requirements of the Common Carbon Metric, and the rating as developed in this document is a suitable point for contribution to the development of this international initiative.

2.3.3 Water Data Coverage

The coverage of the water sample data set was assessed in much the same way as the energy sample data set.

Geographic Location

Distribution of the building responses by geographic region is shown in Table 4 below.

Location	GLA (m2)	% (GLA) of total	No. of Building	Annual kL	% (kL) of total
Johannesburg	1,232,312	46%	105	1,096,015	41%
Pretoria	481,941	18%	50	548,717	21%
Rest of Gauteng	125,029	5%	10	167,105	6%
Western Cape (incl. Cape Town)	488,108	18%	51	497,713	19%
KwaZulu Natal (incl. Durban)	232,540	9%	27	291,665	11%

Other	131,741	5%	15	57,198	2%
Total	**2,691,671**	**100%**	**258**	**2,658,414**	**100%**

Table 4: Distribution of sample data (energy) by geographic region

As Table 4 indicates, the water sample data covers approximately 2.7 million square metres of office building gross lettable area in a total of 258 buildings. The total annual water usage footprint of these buildings was approximately 2.7 million kilolitres (or m^3) of water per year.

The geographic distribution of buildings is presented graphically in Figure 8.

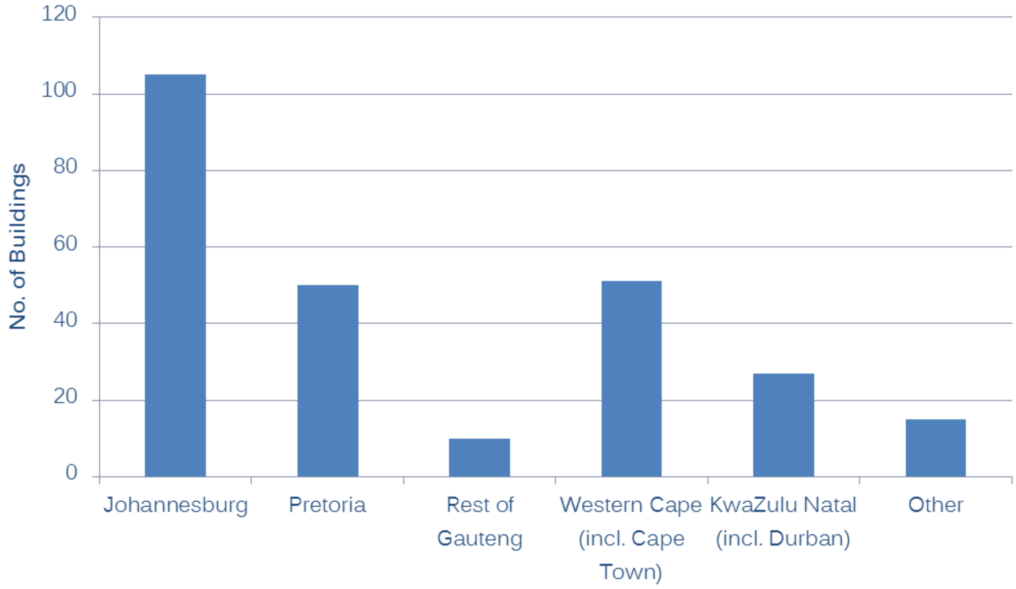


Figure 8: Geographic distribution of sample data (Water)

As is the case for the energy sample data set, respondents are concentrated to the major urban centres (Johannesburg, Pretoria, Cape Town and Durban). This is acceptable as the majority of the office building stock in South Africa is located within these urban centres.

Building Size

As per the examination of energy sample data, the water sample data has been categorised into 6 bins of building sizes, the descriptive statistics for these size ranges are presented in Table 5 below:

GLA Category	No. of buildings	% of total number	GLA (m^2)	% of total sample GLA
0-2,000 m^2	35	14%	39,823	1%
2,001-5,000 m^2	68	26%	242,094	9%
5,001 - 10,000 m^2	62	24%	447,725	17%
10,001 - 20,000 m^2	61	24%	810,757	30%
20,001 - 30,0000 m^2	19	7%	452,288	17%
>30,000 m^2	13	5%	698,985	26%
Total	**258**	**100%**	**2,691,671**	**100%**

Table 5: Distribution of sample data (energy) by building size category

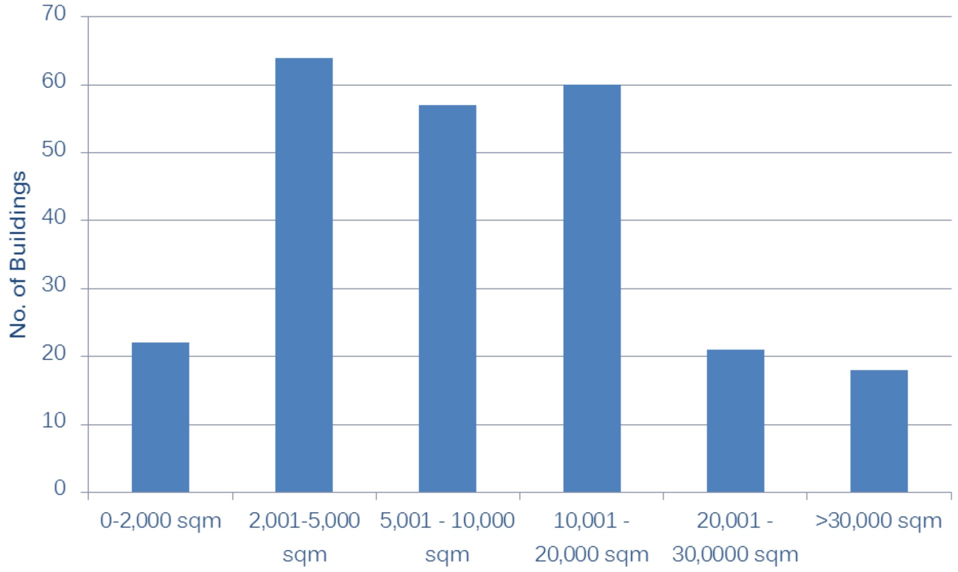


Figure 9: Sample building size distribution by number of buildings (Water)

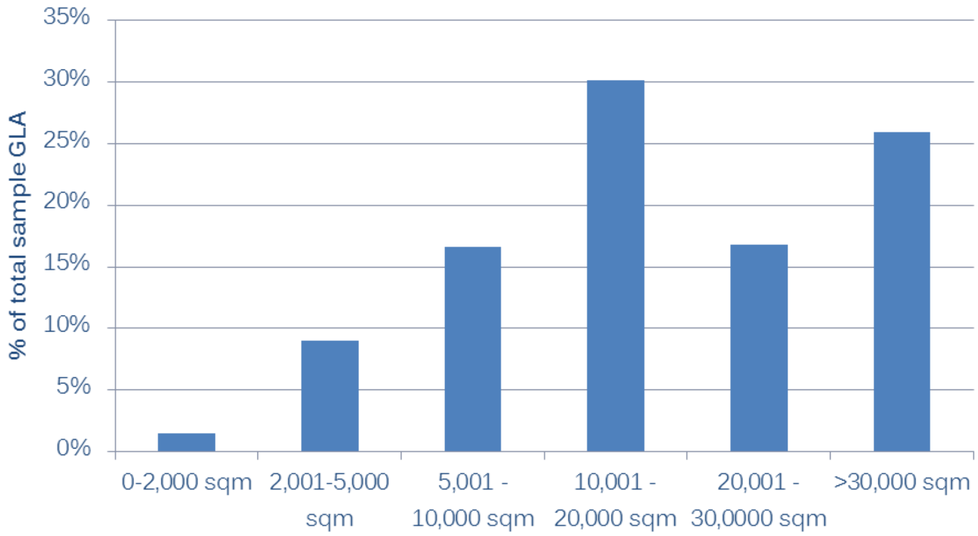


Figure 10: Sample building size distribution by % of total sample GLA (Water)

Similar to the energy sample data set, more data on the smallest office buildings (0-2000 m^2 GLA) would improve size coverage. All other size categories appear well represented.

Water Use Intensity

Water use intensity (WUI) is defined as:

$$WUI\ (kL/m^2)\ =\frac{Annual\ Water\ Consumption\ (kl)}{Building\ Area\ (m^2)}$$

The definition of the terms above vary by application and source but in the context of this report, annual water consumption is the whole building annual water consumption in kL while the building area is the gross lettable area of the whole building in m^2. The sample distribution of WUI is presented in Figure 11 below:

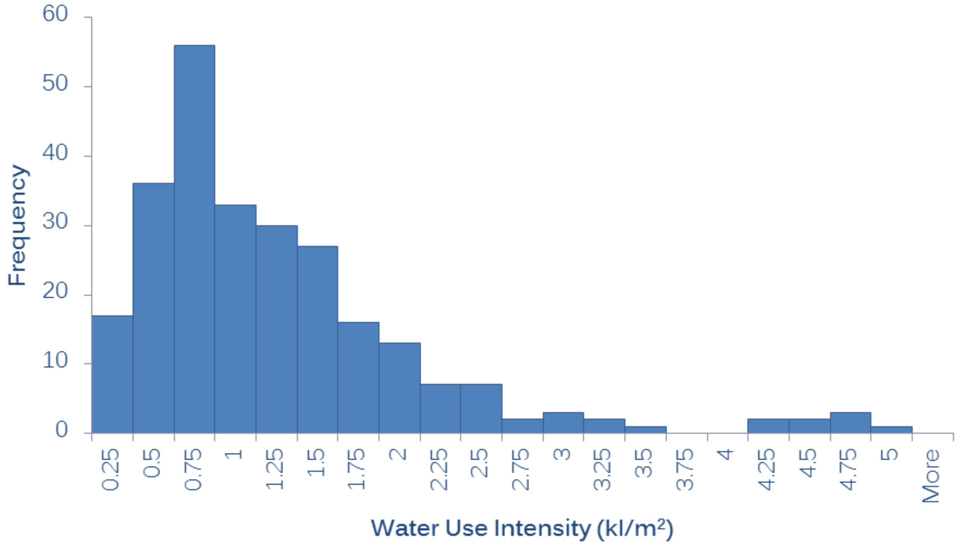


Figure 11: WUI distribution of South Africa office building sample

Figure 11 suggests that there is adequate representation for the full range of WUI; this will enable the definition of a desired distribution for the spectrum of rating outcomes.

3 Energy Demographic Analysis

A large number of factors could potentially drive building energy use and energy efficiency. For the most part, these factors relate to characteristic or operational aspects of a building that may be empirically corrected for in a benchmark rating tool, e.g. building size, operating hours, climate etc. However, building energy efficiency may also be influenced by a number of demographic factors underlying the sample data set which cannot be accounted for (or would be unfair to make a correction for). For example, a building constructed in 1970 may be less efficient than a new building constructed in 2010, purely by virtue of available technologies; nevertheless, building performance cannot be adjusted to account for age as this would remove incentives for older buildings to improve efficiency through refurbishments.

While the full sample data set is limited to information on building location, size and climate zone, the detailed subset provides additional demographic information. It is important that analysis is carried out prior to benchmarking to identify underlying trends between demographic factors and building energy efficiency as these may distort/mislead regression outcomes (e.g. variation in EUI by building location could be misinterpreted as climate effect). Where a significant relationship is identified, the affected data may need to be excluded from subsequent benchmarking. The list of demographic factors to be examined includes:

- Building location
- Building size
- Year of construction or major refurbishment
- % Active cooling
- Energy intensive services (e.g. data centres)

The subsequent sections will analyse each of these demographic variables individually.

3.1 Building Location

The geographic location of the building is directly linked to many intangible social, economic and demographic factors. It is therefore important to examine whether location correlates with EUI in case one or more of these factors influences building energy efficiency.

The following table presents the mean and median EUI for buildings by their location.

Region	GLA	Annual kWh	Mean EUI kWh/m^2	Median EUI kWh/m^2
Johannesburg	1,233,695	300,829,736	213	183
Pretoria	627,582	140,948,632	225	208
Rest of Gauteng	448,815	136,483,566	251	244
Western Cape (incl. Cape Town)	442,513	104,616,327	209	200
KwaZulu Natal (incl. Durban)	265,187	55,365,778	239	208
Other	63,808	12,996,031	182	144
Total	**3,081,600**	**751,240,069**	**219**	**205**

Table 6: Comparison of mean and median EUI by building location

A box and whisker plot is ideal for presenting differences between subsets and has been prepared in Figure 12 to present data distributions by regional classification. Within each regional category, the boxes represent the spread of data between the 25th to 75th percentiles of building EUI while the ends of the whiskers extend to the maximum and minimum intensities observed within that region. The two halves of the boxes meet at the median EUI observed.

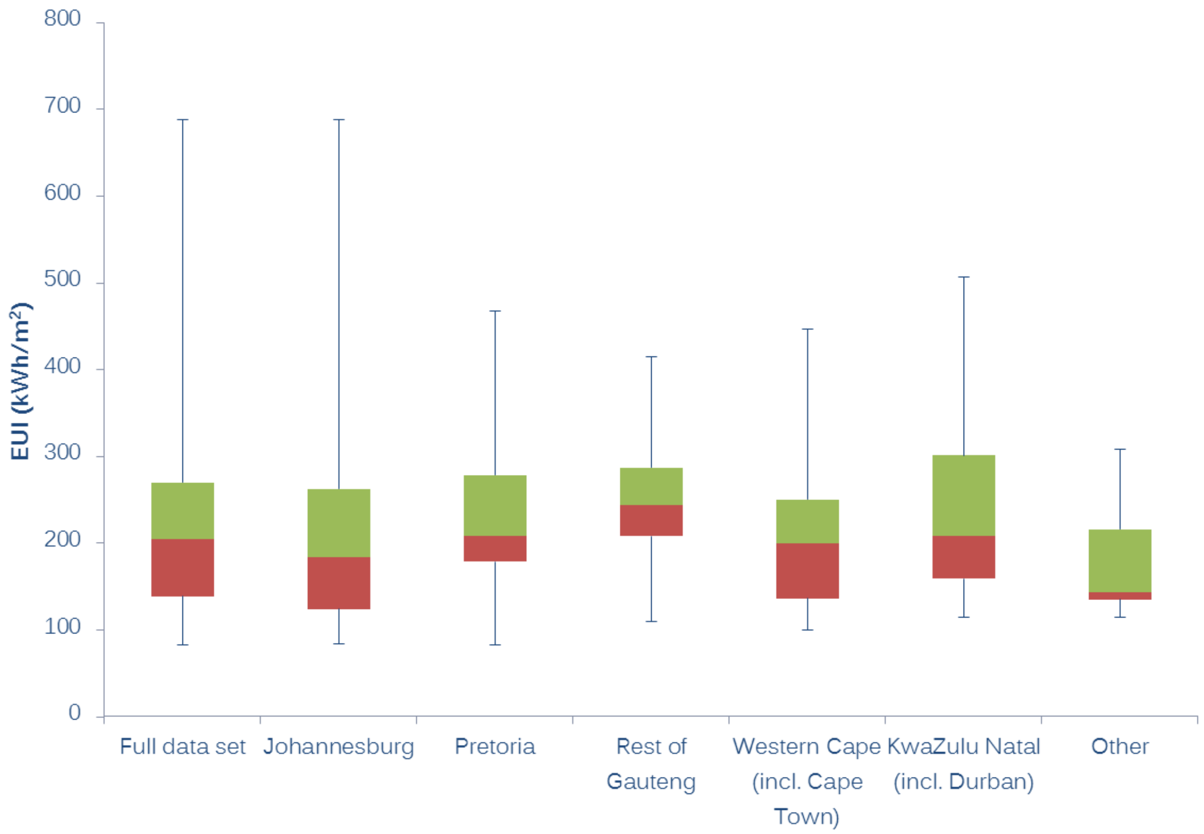


Figure 12: Box whisker plot comparing distribution of EUI by geographic location

Based on data presented in Table 6, the mean and median EUI values appear to vary slightly by location, particularly in the province of Gauteng where the distribution of EUI differs noticeably by location (Johannesburg, Pretoria and Rest of Gauteng).

It is difficult to conclude, based on Table 6 and Figure 12 alone, whether the EUI is strongly affected by location as there is a considerable level of data noise/variability. A two tailed t-test was therefore conducted for each regional subset against the full sample data set to quantitatively assess if the variation in mean EUI for any region is statistically significant. Table 7 summarises the outcomes.

	Mean EUI kWh/m^2	Probability that subset mean equals population mean (p-value)
Johannesburg	213	0.67
Pretoria	225	0.70
Rest of Gauteng	251	0.25
Western Cape (incl. Cape Town)	209	0.55
KwaZulu Natal (incl. Durban)	239	0.35
Other	182	0.29

Table 7: Mean EUI by region and t-test for difference of mean from full sample

The results presented in Table 7 suggest that the mean EUI of the regional subsets do not differ significantly from that of the underlying population (full sample data set). Usually, a difference is significant only when the probability that subset mean=population mean is less than the confidence level, say 0.1 (90% confidence or greater). We can therefore conclude that empirically, building location does not appear to impact building energy efficiency; the relationship is thus unlikely to distort regression outcomes.

3.2 Building Size

The system complexity and level of services provided usually increase with building size, as is the case with the Australian office building stock where larger office buildings are usually "premium" grade to attract higher rental prices. Although the increase in complexity and services may theoretically result in higher EUI, Exergy have found no empirical evidence in its prior office building benchmarking exercises – Exergy have not identified a statistically significant link between building size/quality and EUI on such office building studies. Figure 13 below illustrates that the same can be said for the South African office building stock where the distribution of EUI by building size is extremely noisy and the correlation between building size and EUI insignificant.

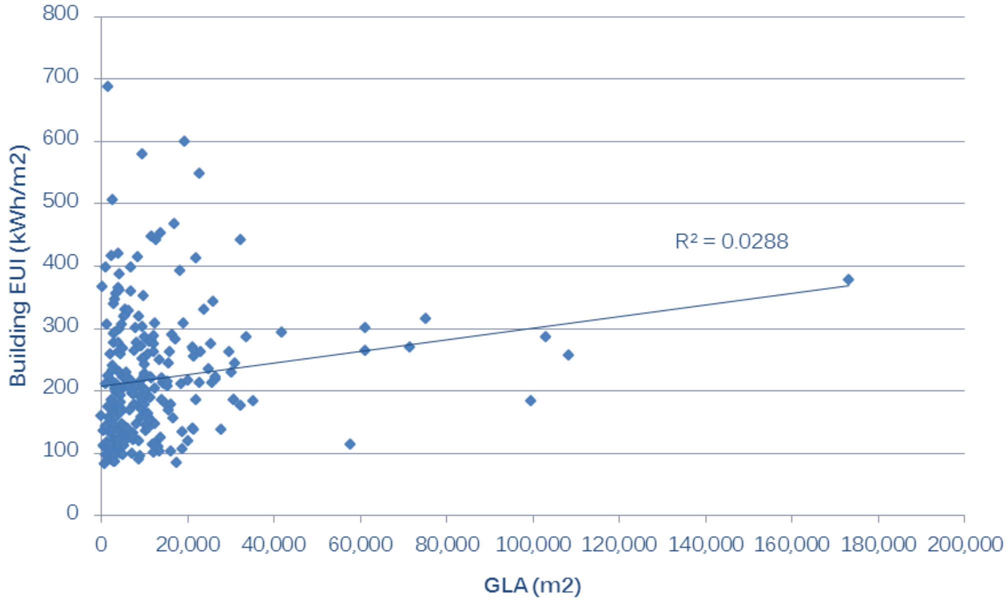


Figure 13: Building size (GLA) vs. EUI

Based on the weakness of the correlation between building size and EUI, it is safe to conclude that building size is not a significant contributory factor in building energy efficiency. Moreover, the lack of correlation between EUI and building GLA provides assurance that the relationship between GLA and kWh is linear.

3.3 Year of Construction or Major Refurbishment

Recently constructed or refurbished buildings often promise improved energy efficiency but as previously stated, a performance benchmark tool cannot and should not correct for this (i.e. allow older buildings to perform poorer) as it would remove energy efficiency incentives in older buildings. Figure 14 below plots the year of construction or last major refurbishment against building EUI.

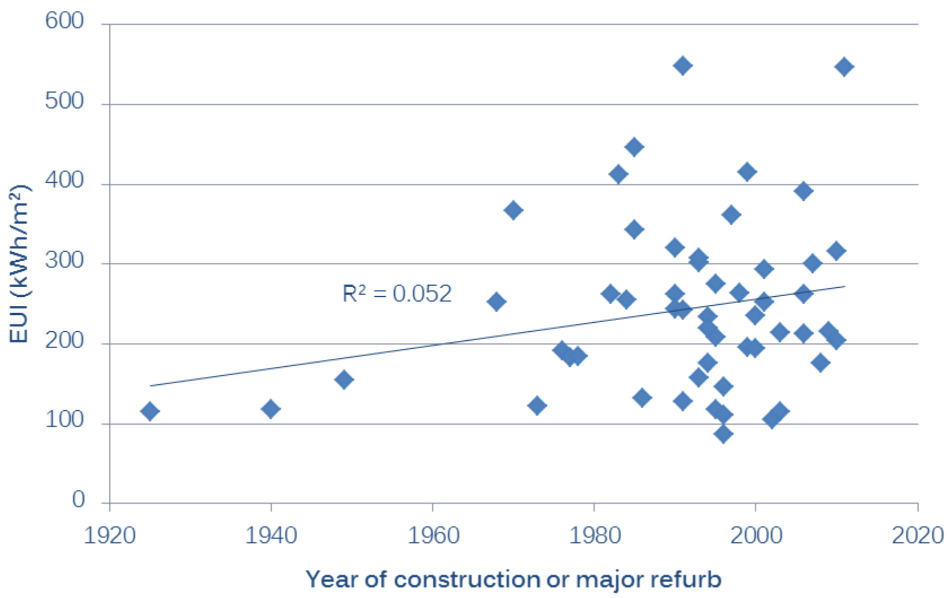


Figure 14: Year of construction or major refurb vs. EUI

Although newer buildings may provide improved energy efficiency, Figure 14 shows a negligible empirical relationship between year of construction/refurbishment and building EUI (note the low R^2 value). The apparent positive slope of the trend line is of no significance, being driven by essentially only three data points. The year of construction/refurbishment therefore has any no significant impact on building energy efficiency.

3.4 % Active Cooling

Building HVAC services vary from natural ventilation only to mechanical air conditioning only and anywhere in between. As part of the questionnaire, respondents were asked to specify the % of total building area covered by the building's active air conditioning system. This information is helpful in identifying atypical buildings within the data (e.g. little or no active cooling) and whether these are likely to cause any discrepancies in subsequent benchmark analysis.

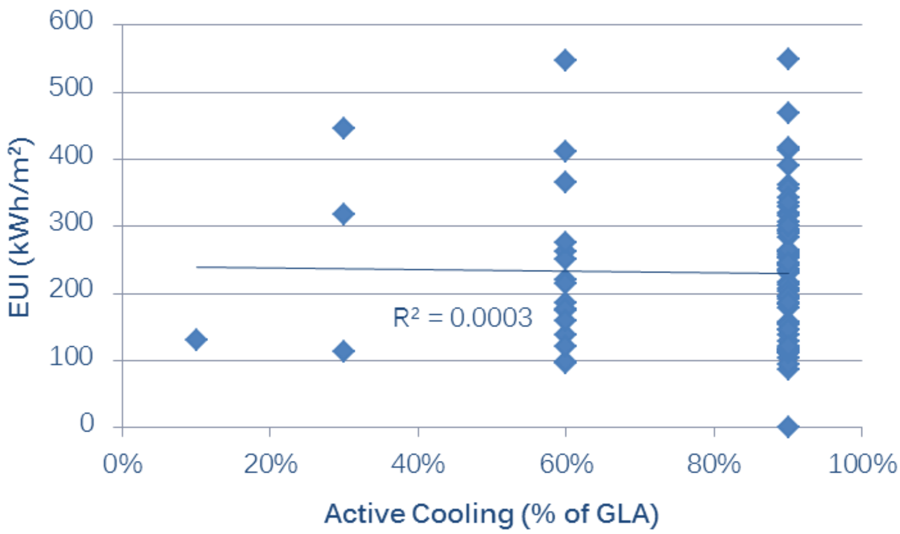


Figure 15: Impact of % active cooling on building EUI

Figure 15 indicates that the % coverage of active air conditioning makes little or no difference in building energy efficiency. This outcome was unexpected but there are two possible explanations:

- Respondents may have misinterpreted the questionnaire and responded with the % of active A/C provided by the base building (building owner) and neglected to include coverage of tenant installed active A/C units.
- Tenant installed equipment and services may be negating any reduction in EUI achieved through natural ventilation and/or passive cooling.

It should also be noted that there are very few buildings with less than 50% active cooling so the impact of these buildings on the benchmark model will be minimal.

In conclusion, it is not necessary to exclude buildings based on their active A/C coverage.

3.5 Energy Intensive Services

The questionnaire also asked buildings to indicate whether there are any energy intensive services operating within the building that is not typically found in office buildings, for example data centres and call centres. Where these end uses are present and significant, it is expected to impact on building EUI. Figure 16 below shows building EUI against existence of non-office energy intensive services.

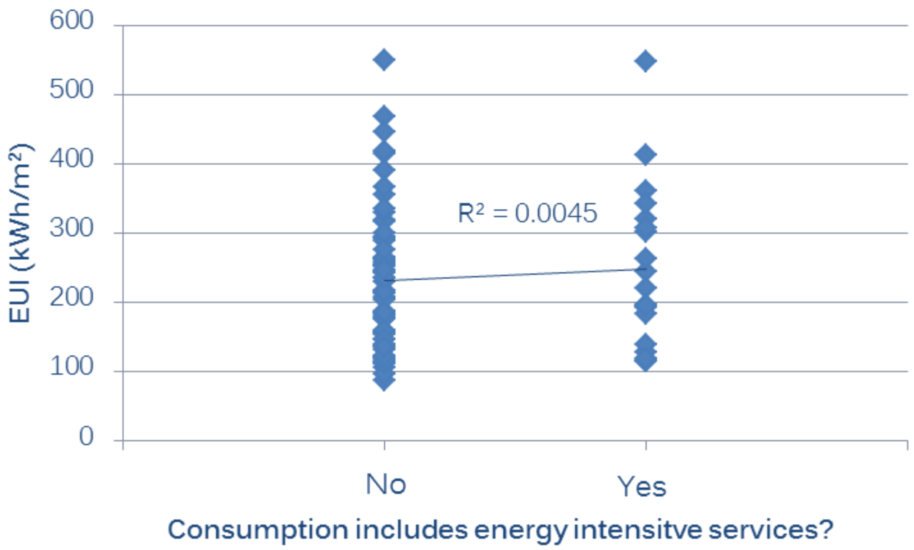


Figure 16: Impact of energy intensive services on building EUI

While the inclusion of energy intensive services such as data centres will contribute to a building's EUI, the empirical evidence in Figure 16 suggests that there are no discernible differences in EUI between buildings with and without these services. There are a couple of potential explanations:

- The scale of consumption by these energy intensive end uses is lower than expected and are not comparable to whole building energy consumption, i.e. in most cases, they only account for a small fraction of the whole building consumption.
- The building owners/operators are misinterpreting the questionnaire and including small end uses under this classification.

Despite the lack of empirical relationship, it is nevertheless important to facilitate exclusion of high intensity non-office energy consumption in a formal rating tool for fairness of comparisons. However, given that the rating will likely be based on GLA which include non-office end uses such as retail, clarity in the definition of applicable exclusions is paramount.

3.6 Analysis with Full Data Set vs. Detailed Subset

While the combined data set consisting of both basic and detailed data is useful in assessing sample quality and determining primary correlations (i.e. average EUI), the basic data subset (size, location and consumption only) lack the details required for robust residual analysis. The detailed data subset on the other hand is based on survey responses and provides a list of applicable factors for further consideration (see Section 4.2); the detailed analysis for significant consumption drivers is therefore limited to these survey responses. Prior to analysing the detailed subset, it should first be assessed for bias and representativeness; if the subset is found to be unbiased and representative of the full sample, then inferences based on residual analysis of this smaller set of data is directly applicable to the broader sample and perhaps the population. If however the detailed subset data is a biased sample of the full data set, then care must be taken in interpreting analysis outcomes as they may be influenced by the underlying sampling bias.

The subsequent sections will conduct both qualitative and quantitative analyses to ascertain any statistical differences between the full sample data set and the detailed data subset.

3.6.1 Geographic location

The distribution of buildings by geographic location is presented for both the full data set and the detailed subset in Figure 17 and Figure 18 below.

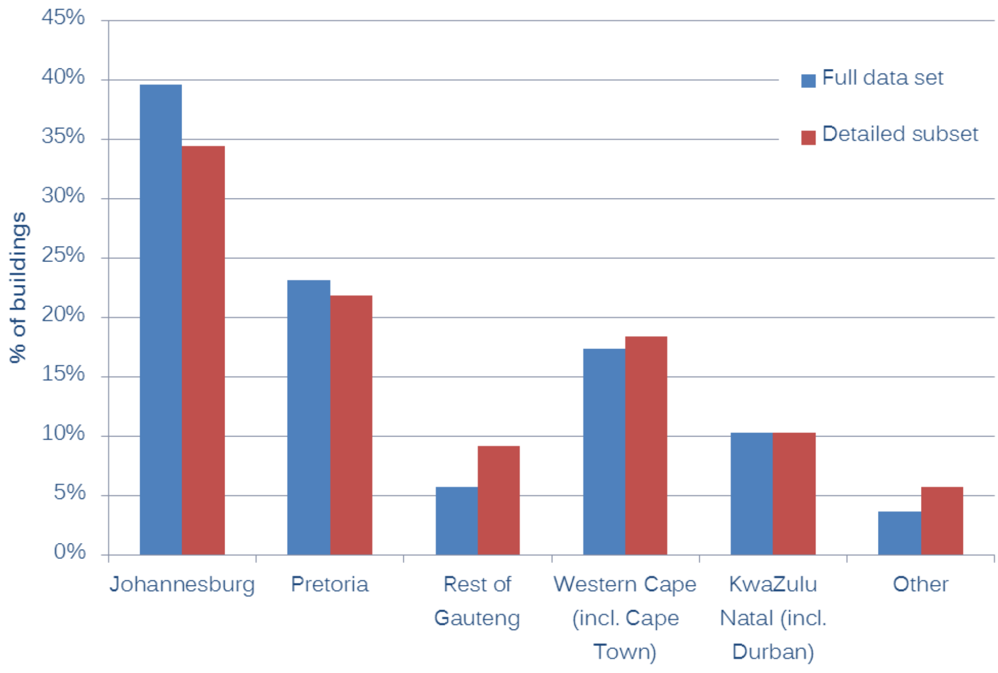


Figure 17: Full vs. detailed sample data – comparison of geographic distribution by number of buildings (%)

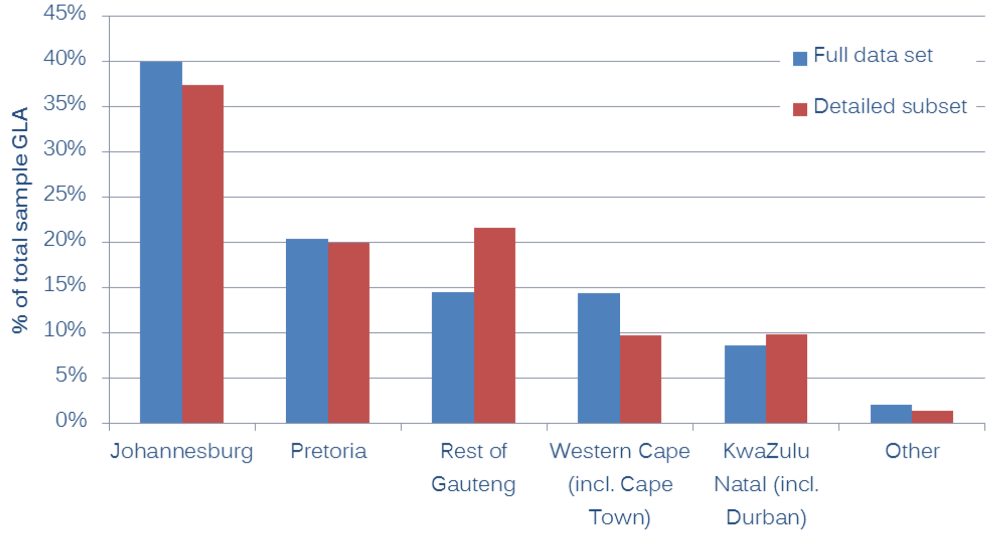


Figure 18: Full vs. detailed sample data – comparison of geographic distribution by % of sample GLA

The plots above indicate that there is no significant difference in proportional coverage of the sample data by geographic location (either by number or GLA covered). Minor differences in data distribution are attributable to variability in sampling. With regards to geographic coverage, it is safe to conclude that the detailed subset is representative of the full data set.

3.6.2 Building size

The distribution of buildings by size category is presented for both the full data set and the detailed subset in Figure 19 and Figure 20 below.

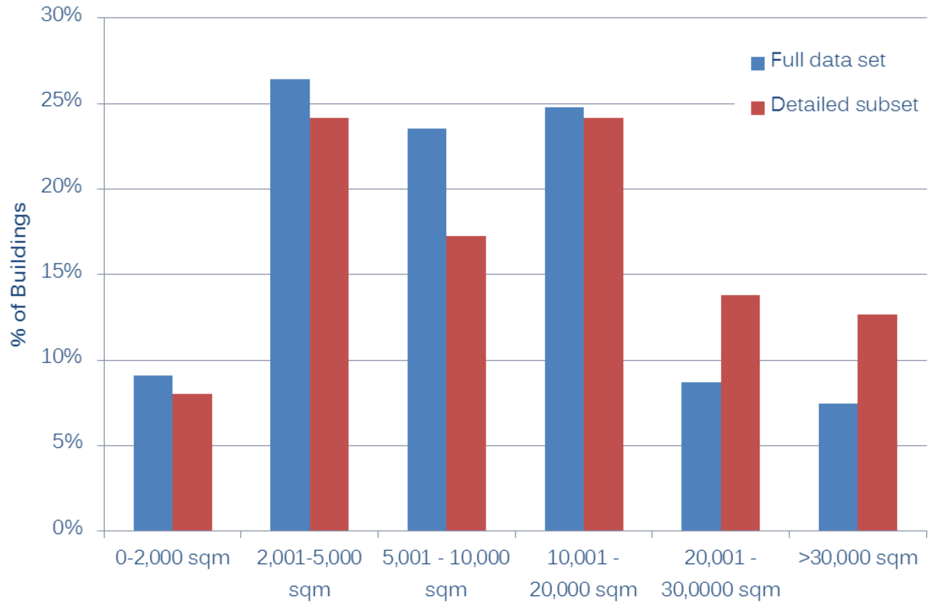


Figure 19: Full vs. detailed sample data – comparison of building size by number of buildings (%)

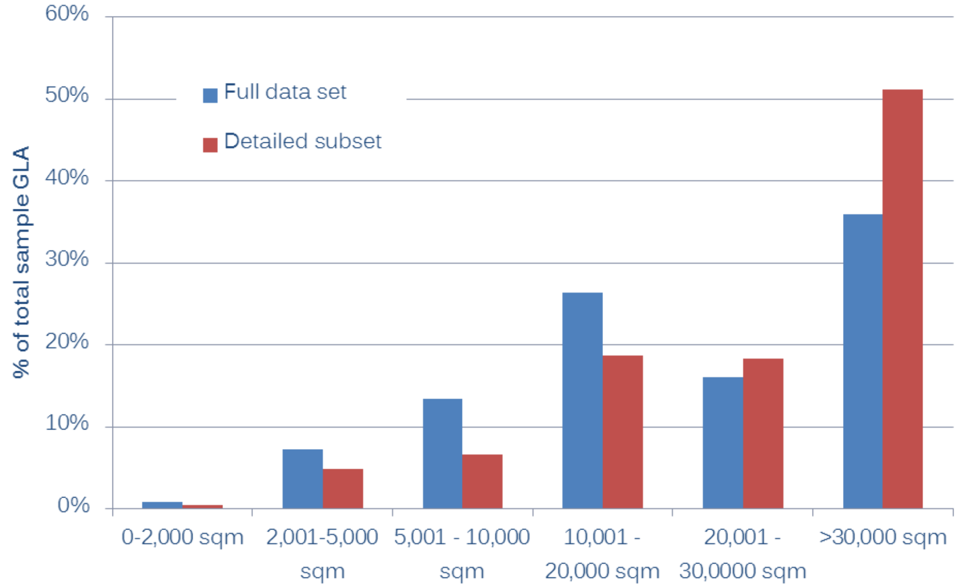


Figure 20: Full vs. detailed sample data – comparison of building size by % of sample GLA

Based on the plots above, the detailed subset of sample data is slightly biased towards the larger building sizes. Inferences made based on the detailed subset only will therefore be more applicable to larger building sizes; this is not expected to invalidate any subsequent analysis on the detailed subset as building size does not appear to correlate with EUI (see Figure 23).

3.6.3 EUI

It is essential that the distribution of EUI and WUI for the detailed sample does not differ significantly from the full data set; if the difference is statistically significant, inferences made based on the subset data will be subject to sampling bias and therefore invalidated. For example, if the average EUI for the detailed subset is lower than the average EUI of the full data set, then the buildings from the detailed subset are deemed to be more efficient than the population "average" building, Any subsequent analysis would be unrepresentative of the larger sample, and ultimately the larger population.

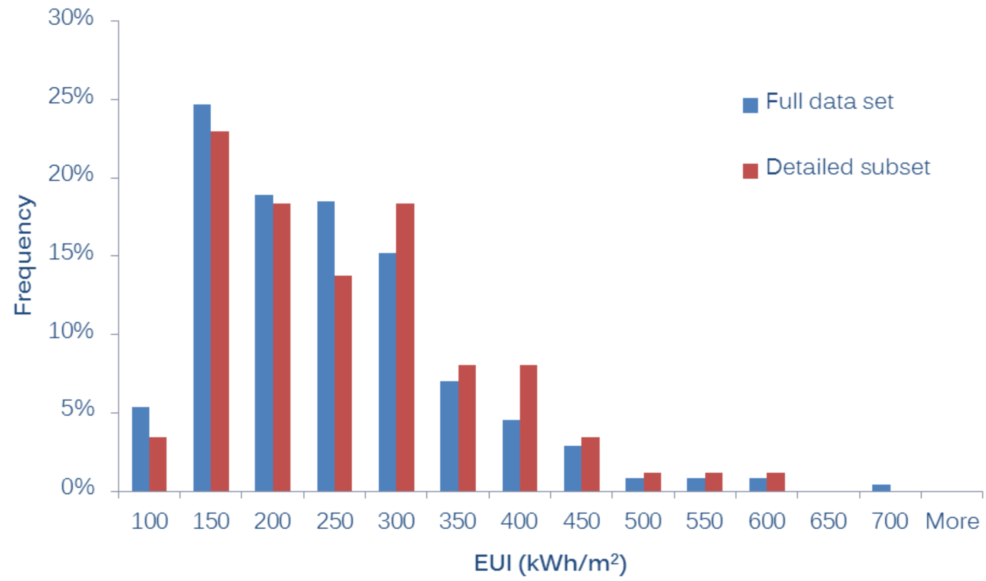


Figure 21: Full data set vs. detailed subset – comparison of EUI distribution

Qualitatively, Figure 21 does not suggest that there is a significant difference in EUI distribution between the full data set and detailed subset. Quantitative analysis is necessary to confirm this observation. A two tailed t-test can be used to assess whether there is a significant difference between the mean EUI underlying the two data sets. The two tailed t-test returns the probability that the null hypothesis is true i.e. the probability that the two sample means are equal. The output of the two-tailed t-test is presented in Table 8 below.

	Full data set kWh/m²	*Detailed subset kWh/m²*
Mean	219	234
Variance	10400	11300
Observations	242	87
Hypothesized Mean Difference	0	
t Stat	-1.13	
P(T<=t) two-tail	0.259	

Table 8: two tailed t-test output for mean EUI of full data set vs. mean EUI of detailed subset

The high probability (~0.26) suggests that the null hypothesis cannot be rejected, i.e. the mean EUIs underlying the two data sets are not significantly different.

Based on the evidence of qualitative and quantitative comparisons in the EUI distributions, there is reasonable confidence that the detailed subset is an unbiased and representative subset of the full sample.

3.7 Conclusion

A number of demographic factors and their impact on building EUI were examined in the preceding sections. The results of the empirical analysis show that variations in sample building EUI were not subject to the influence of any demographic factors such as building location, building size, year of construction/refurbishment, % of active cooling coverage and inclusion of energy intensive end uses. This outcome provides reassurance that subsequent empirical modelling is unlikely to be affected by demographic influences underlying the sample data set.

Based on the similarities identified between the full data set and the detailed subset, there is sufficient grounds to conclude that inferences made based on the detailed subset is reasonably representative of the broader sample and population of office buildings in South Africa. While there is a slight sampling bias towards larger buildings, subsequent residual analysis based on the detailed subset should yield unbiased estimates for the underlying relationships between key variables and EUI.

4 Energy Benchmarking Methodology

The purpose of the benchmark model is to compare energy consumption of buildings with different characteristics. Using a few input parameters that characterise a building's physical and operational characteristics, the benchmark model aims to predict the expected (population average) energy consumption for a building with the given characteristics.

In constructing the benchmark model, the key objective is to explain the variability in building energy data using a number of key consumption drivers derivable from building characteristics data. Potential consumption drivers are selected from a list of variables underlying the basic and detailed sample data including size, climate, operating hours.

4.1 Correcting Energy Consumption for Building size

Building energy consumption increases with building size; this is a scale relationship that is fundamental to all existing energy rating tools. Specific to the South African data set, there are two approaches to account for the impact of building size on energy consumption, either 1: a linear correction for kWh based on its correlation to GLA or 2: size normalisation of kWh by GLA, i.e. working with EUI (kWh/m^2). Both methods offer means of providing a first order estimate for a building's energy consumption.

The correlation between whole building kWh and GLA is presented in Figure 22 below.

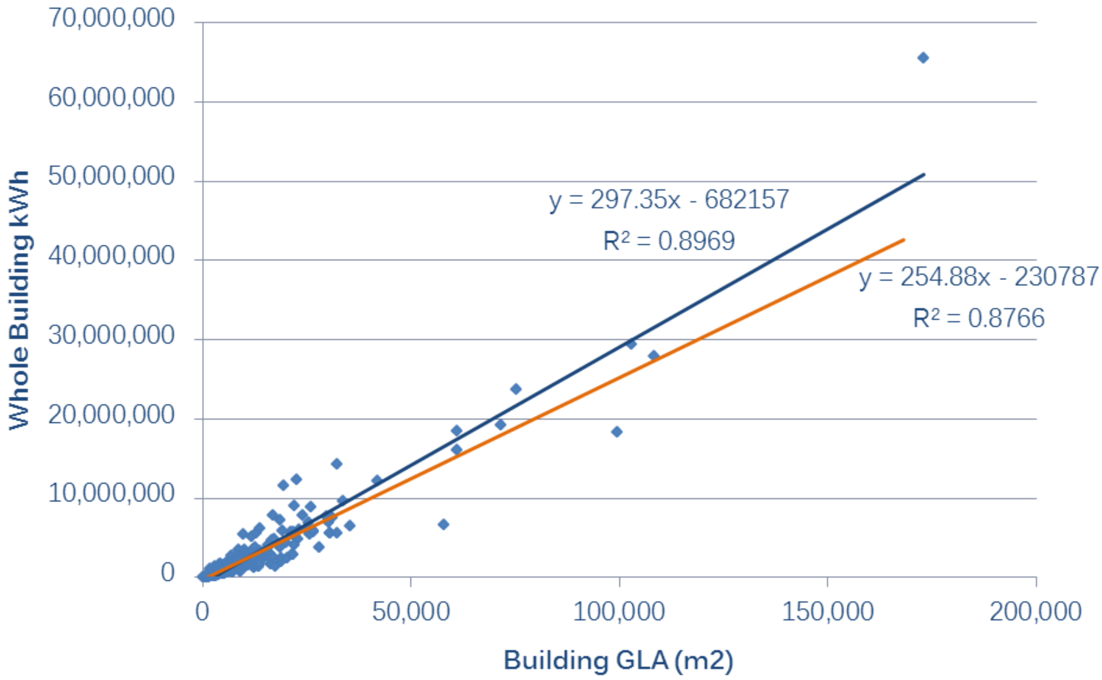


Figure 22: Building annual kWh energy consumption distributed by building size (GLA)

While the data in Figure 22 shows the expected strong correlation between building size and energy consumption, there are several risks in estimating/predicting building kWh with GLA.

- Although strong, the linear relationship (and any linear regression analysis based on the relationship) is heavily and disproportionately influenced by the larger buildings. This is evidenced by a significant change in the trend line when the largest site is removed (equation would be $y = 254.88x - 230787$ denoted by the orange line).
- While the model explanatory power is expected to be excellent (indicated by the high R^2 value), the noise (variation in kWh consumption above and below the fitted line) is increasing with building size, i.e. note the slight fan shape in the data distribution. This is characteristic of size correlated data where proportional errors are often observed. The increasing variance in observations violates linear regression assumptions and will consequently reduce model validity during analysis.

The alternative approach to first order estimates of building energy consumption is to normalise energy consumption by building size, i.e. work with EUI (kWh/m^2). By evaluating the EUI for each building, the energy consumption is normalised by size and this in turn avoids the two size related issues previously listed. In this instance, the expected EUI for a building is the sample average EUI in kWh/m^2; the expected annual energy consumption is determinable by multiplying with GLA.

Figure 23 below demonstrates the insignificant correlation between building size and the normalised energy consumption, EUI. The average EUI of 219kWh/m^2 has also been identified on the plot.

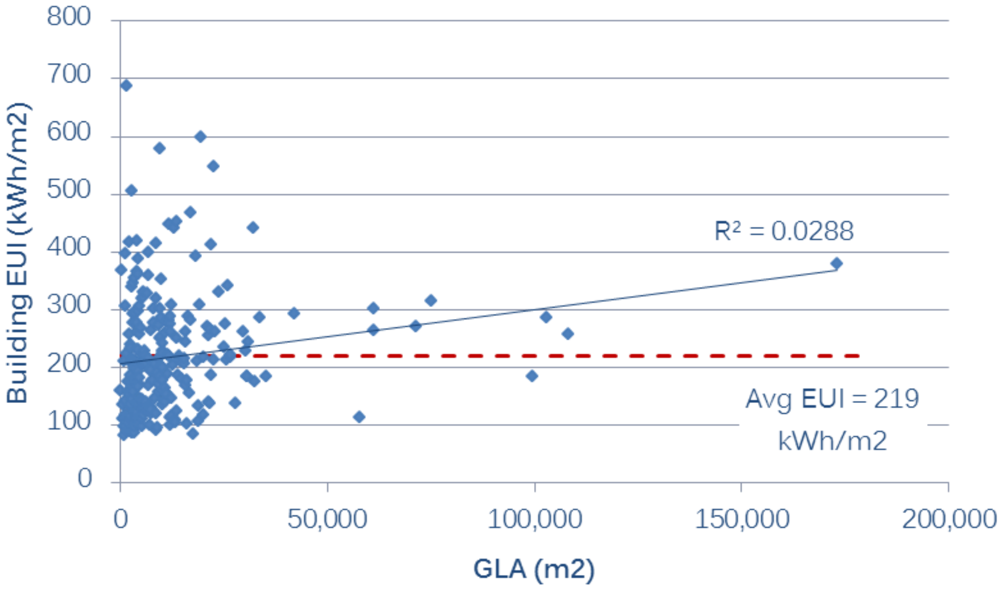


Figure 23: Building EUI distributed by building size (GLA)

The figure above also shows that under the normalised energy approach, the larger buildings in the dataset do not exert excessive influence; where the largest site was previously considered an outlier/influential point in Figure 22; once normalised, its energy intensity is clearly within a reasonable range.

Based on the preceding arguments, the primary correction for scale data should be via the use of EUI which is normalised for building size. The first order estimate for the expected EUI of a given building is therefore:

$$Expected\ EUI\ =\ Sample\ Average\ EUI = 219\ kWh/m^2$$

Furthermore, the first order estimate for the expected energy consumption of a given building is:

$$Expected\ Annual\ kWh = Expected\ EUI \times GLA = 219 \times GLA$$

This is equivalent to drawing a straight horizontal line as shown in Figure 23 at 219 kWh/m^2. Buildings above this line have higher EUI than average while those below this line have lower EUI than average. The difference between the observed/measured EUI for each building and this average EUI is called the residual. The residual ε relates to actual building energy consumption in the following way:

$Actual\ EUI = Expected\ EUI + \varepsilon$, OR **Equation 1**

$$Actual\ Annual\ kWh = (Expected\ EUI + \varepsilon) \times GLA$$

Residual analysis is conducted against a range of other potential consumption drivers to identify any underlying trends in the building EUI. Clearly, EUI does not correlate strongly with building size.

4.2 Residual Analysis with Detailed Subset

The objective of the residual analysis is to explain as much of the variation in residual EUI as possible using a number of potential consumption drivers identified in the detailed subset data. Where a significant relationship exists, the relevant consumption driver(s) can be used to further improve model predictions

Carrying on from Equation 1 in Section 4.1, residual EUI, ε is defined as

$$Actual\ EUI = Expected\ EUI + \varepsilon$$

$$\varepsilon = Actual\ EUI - Expected\ EUI$$

The following sections will investigate a list of potential consumption drivers for correlation with residual EUI in a process that seeks to improve benchmark model explanatory power and reduce the uncertain noise term, ε. The list of potential consumption drivers include:

- Climate
- Occupancy hours
- Computers density (computers per m^2 GLA)
- Occupant density (occupants per m^2 GLA)
- Lettable office space (% of GLA)
- Vacancy rate (%)
- Car park density (car parks per m^2 GLA)

Note that where possible, the variables have been normalised for building size, e.g. computer density, occupant density, % lettable office space etc. This is called for in residual analysis as residual EUI is already normalised for size.

4.2.1 Climate

4.2.1.1 Empirical data

The impact of climate on building energy consumption warrants detailed analysis and discussion. The potential impacts of climate on efficiency of building services is a point of contention for many benchmark studies and although fundamental theory may suggest that climate should affect building energy efficiency, there has been a general lack of empirical evidence supporting this claim. To investigate the empirical impact of climate on energy efficiency in South African office buildings, metrics for cooling load and heating load of climate zones, i.e. Cooling Degree Days (CDD) and Heating Degree Days (HDD), were compared against building residual EUI for correlation. Note that climate data (based on postcode) was available for the full sample data set so this analysis is not limited to the detailed subset.

Annual CDD is the integral of all the time <u>above</u> a baseline temperature, over a year; simplified it is:

$$CDD = (Temperature - Base\ Temperature) * Days\_Elapsed \qquad \textbf{Equation 2}$$

For example, if the base temperature was 15°C, and one day was a constant 25°C, this would be 10 Cooling Degree Days (10 degrees * 1 day). Similarly, one hour at 40 degrees would be (40-15)*(1/24), or 1.04 CDD. The annualised CDD is therefore the integral of the temperature deviations over a one year period. Base temperatures may be in either wet bulb or dry bulb pending type of application.

The definition of annual HDD is much the same as CDD, except that it is the integral of all the time below a baseline temperature, over a year; simplified it is:

$$HDD = (Base\,Temperature - Temperature) * Days\_Elapsed \qquad \textbf{Equation 3}$$

Locations with high annual CDD usually signify cooling-dominated climates where additional cooling load and decreased HVAC cooling efficiency could lead to higher EUI. Similarly, locations with high annual HDD usually signify heating dominated climates where additional heating loads could also lead to higher EUI. These relationships often lead to empirical correlations between EUI and CDD or HDD, which when quantified, would form the basis of climate corrections.

Annual CDD (14˚C wet bulb base temperature) has been plotted against building EUI data in Figure 24 below. Note that climate data was not available for a few buildings located in regional areas.

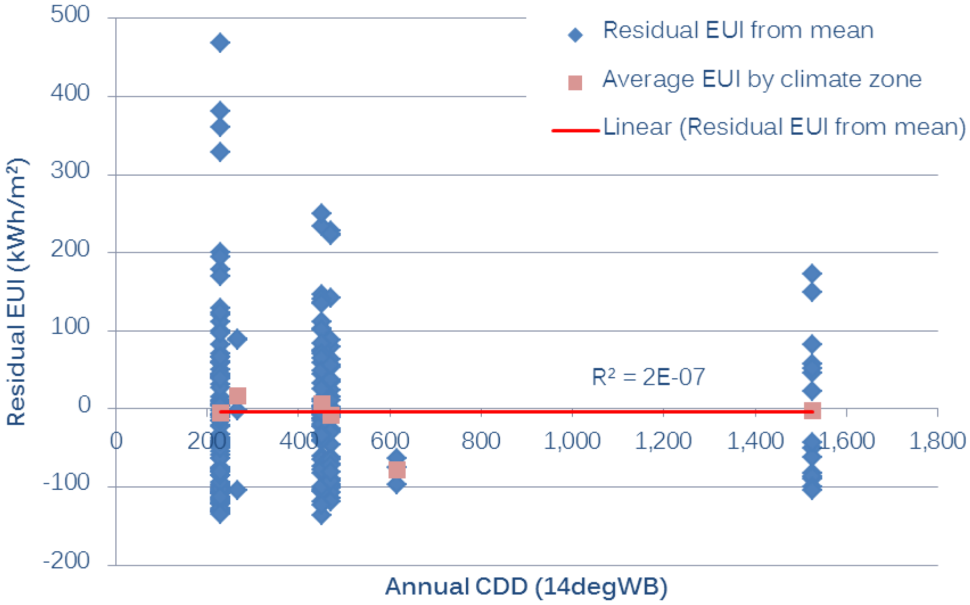


Figure 24: Correlation between annual CDD and residual EUI

Figure 24 illustrates that the sample buildings fall into only a few climate zones across South Africa with annual CDD values ranging from 230 to 1526. The average EUI for each climate zone has also been identified on the plot for clarity; based on the distribution and the flat trend line above, there is no correlation between cooling demand (CDD) and EUI. There is therefore inadequate justification for a climate correction based on annual CDD.

Annual HDD has been plotted against building EUI data in Figure 25 below. Note that climate data was not available for a few buildings located in regional areas.

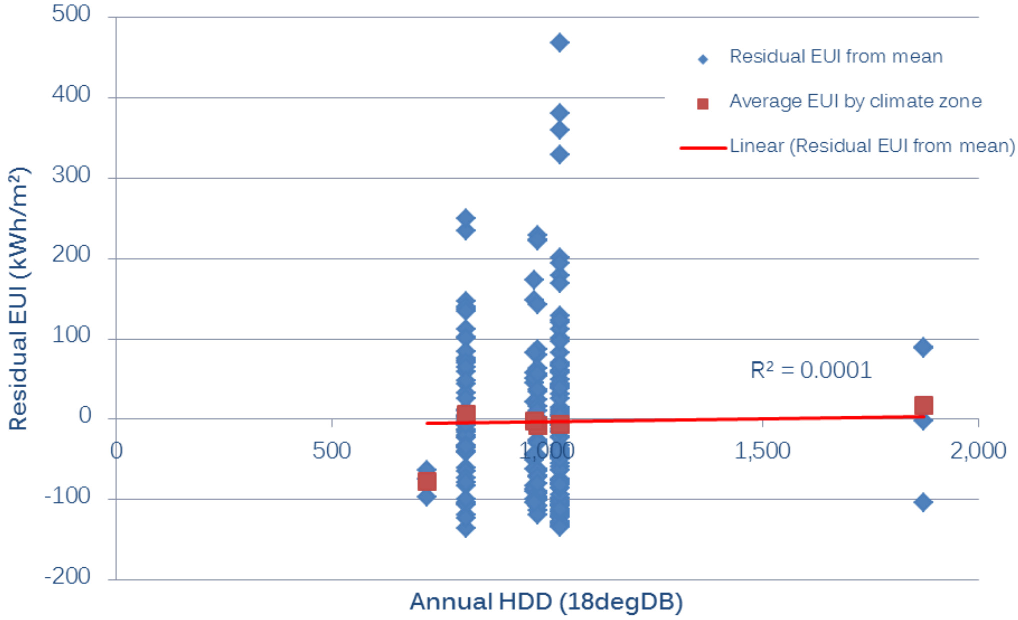


Figure 25: Correlation between annual HDD and residual EUI

Similarly, based on the outcomes presented in Figure 25, there is no empirical justification for a climate correction based on annual HDD.

In electricity dominated building markets, it is also important to examine correlation of energy intensity against the sum of the CDD and HDD which is a rough proxy for the total HVAC load expected. Figure 26 below presents the correlation between combined CDD/HDD and residual EUI (kWh/m^2)

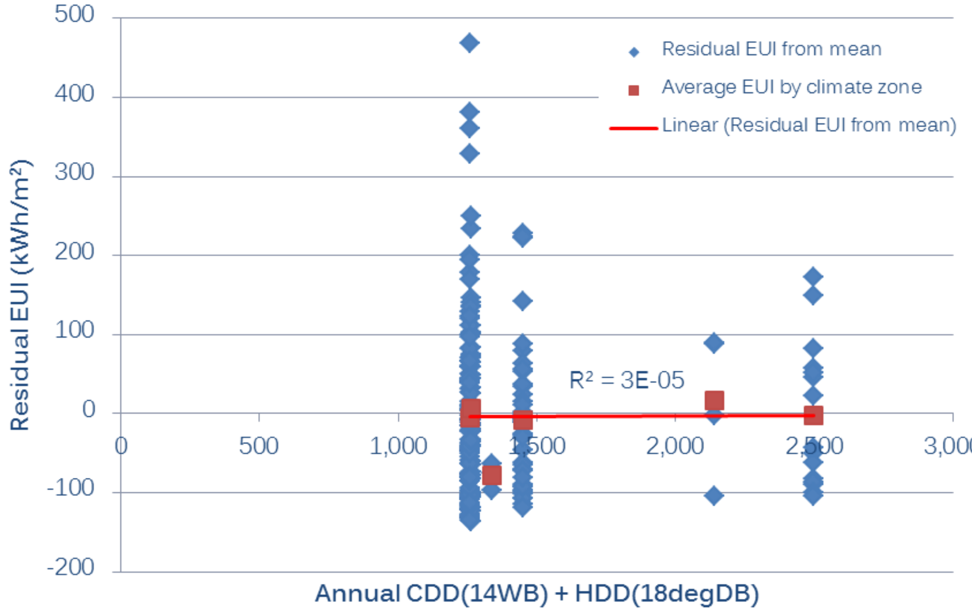


Figure 26: Correlation between CDD+HDD and residual EUI

There are several explanations for why there is little empirical evidence of climate impact on building energy efficiency.

- HVAC services are prone to a number of failure modes; even the smallest inefficiencies/failure can easily outweigh any climate effects.

- In extreme climates, building HVAC systems are usually simpler, leading to a significant reduction in building service conflicts and thus improved building energy efficiency.
- The diversity in the range of observed CDD and HDD is quite limited.
- In South Africa, since the office building market is almost entirely supplied by the electricity grid (little or no alternative fuel use), increased energy consumption (and EUI) would be observed for both cooler and warmer climates that provide more heating and cooling respectively. This will lead to reduced differentiation in EUI for buildings in different climates.
- The effect of climate on energy consumption is further reduced by the inclusion of tenancy energy consumption which is independent of climate.

Although there is no empirical support for a climate correction, some recognised international energy efficiency ratings tools have nonetheless chosen to adopt theoretical corrections in response to concerns raised by the property sector. A similar approach has been adopted in the South African benchmark and this is presented in Section 4.4.

4.2.2 Occupancy Hours

Building services operate different hours and days depending on scheduling, leasing requirements and tenant occupancy patterns. In theory, buildings that operate longer hours are expected to consume more energy and thus more energy per square metre. Some international rating tools in incorporate a purely theoretical correction for building hours.

As part of the detailed data set, owners/operators were asked to indicate the number of hours per week their buildings were required to operate (e.g. provide air conditioning) when the building was mostly occupied. Of the 83 sites in the detailed subset, all sites were able to provide an indication of their operating hours; the responses are presented in Figure 27 below.

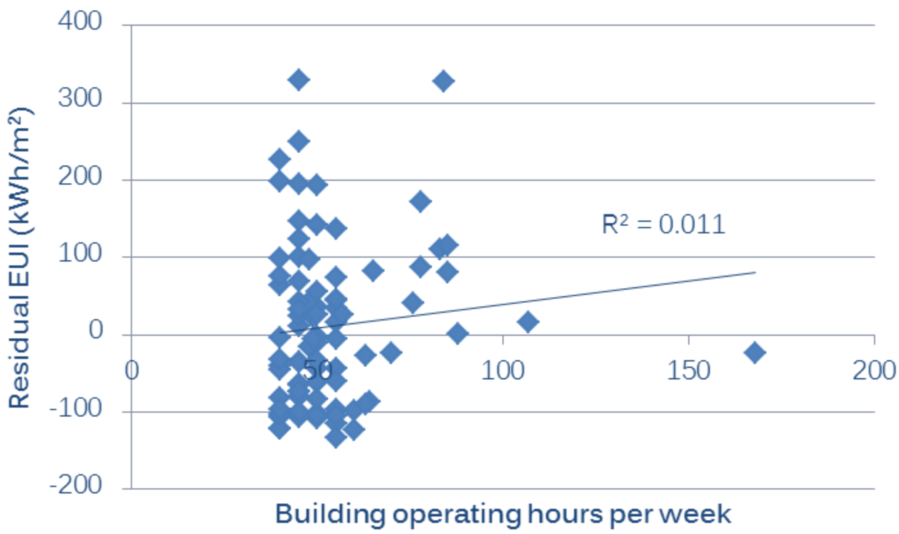


Figure 27: Correlation between building operating hours and residual EUI

Based on the residual distribution, there is weak empirical correlation between building operating hours and building performance. However, there are several justifications favouring a theoretical correction despite the lack of empirical evidence:

- There is poor resolution and questionable reliability in occupancy driven operating-hours data collected via the questionnaires. Even during a formal assessment, the building's assessable operating hours, and whether these hours reflect actual occupancy, can be difficult to ascertain at times, especially if also taking after-hours occupancy into account.
- The limited diversity in building hours (largely in the 45-65 hour range) also contributes to the weak correlations. There are only a small handful of buildings operating longer than 65 hours per week and while these hint at a probable trend, there is insufficient evidence to proceed with further empirical analysis.
- There is strong theoretical basis and empirical evidence from building energy simulations that extended hours of operation can have considerable impact on energy consumption.

For these reasons, a theoretical correction based on building simulation outcomes should be used in the absence of empirical evidence; this is further explored in Section 4.3.

4.2.3 Computer density

The total number of computers is corrected for under some international rating tools. As the total number of computers increase, it is expected that energy consumption (building services and equipment energy) would increase correspondingly. The computer density is also a good proxy for factors such as total equipment density and how much necessary servicing the building is providing to satisfy its tenants. Computer density also has the distinct advantage that it is a metric that is directly related to energy consumption (i.e. more computers means higher energy consumption); moreover, it's easily measurable and auditable.

Of the 83 sites in the detailed subset, 54 sites were able to provide a count for the number of computers in the building; the responses are presented in Figure 28 below.

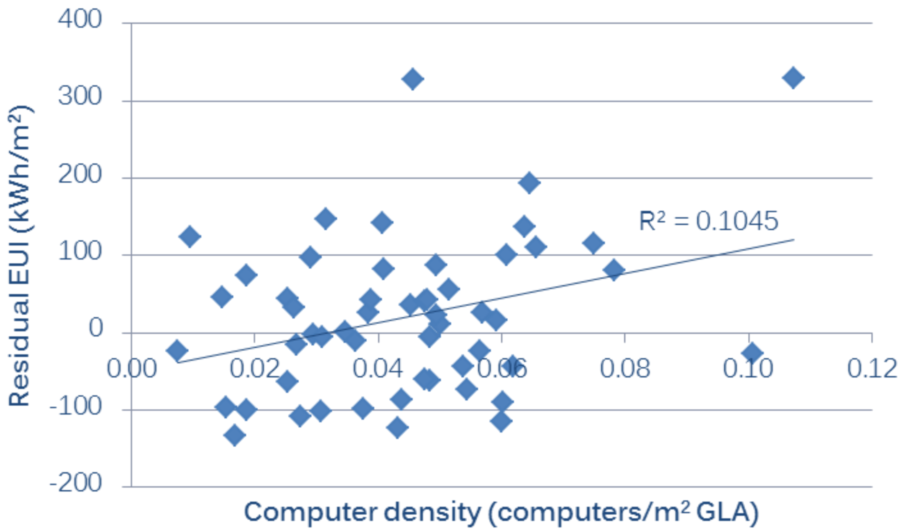


Figure 28: Correlation between computer density and residual EUI

Figure 28 shows a positive correlation between residual EUI and computer density; there is a noticeable trend that buildings with higher computer density have higher energy intensity. While it is difficult to conclude based on this plot alone the significance of the relationship, it identifies computer density as a candidate for further regression analysis and potential inclusion in the benchmark model. This is discussed further in Section 4.5.1.

4.2.4 Occupant Density

This variable is analogous to computer density (as it can be assumed that occupants usually work with at least 1 computer) and is also useful as a proxy of how much necessary servicing the building provides. The following figure demonstrates the strong cross-correlation between computer density and occupant density; note that only 53 sites were able to provide counts for both occupants and computers.

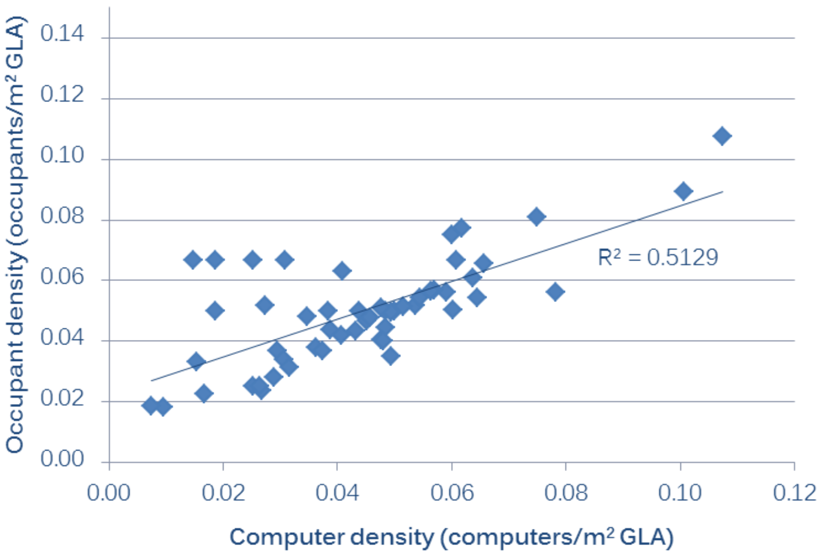


Figure 29: Cross correlation between computer density and occupant density

The strong cross correlation in Figure 29 means that computer density is directly proportional to occupant density, but it also means that since the two factors are not independent, only one of the two factors can be included in the final benchmark model. Notably, occupant density is much more difficult to measure and verify in a rating tool since people move in and out of buildings while in some cases, adjusting for part time workers may prove difficult. Furthermore, as computers directly use energy while occupants merely increase service requirements, computers are a more directly physical correlator.

Of the 83 sites in the detailed subset, 74 sites were able to provide a count for the number of occupants in the building; the responses are presented in Figure 30 below.

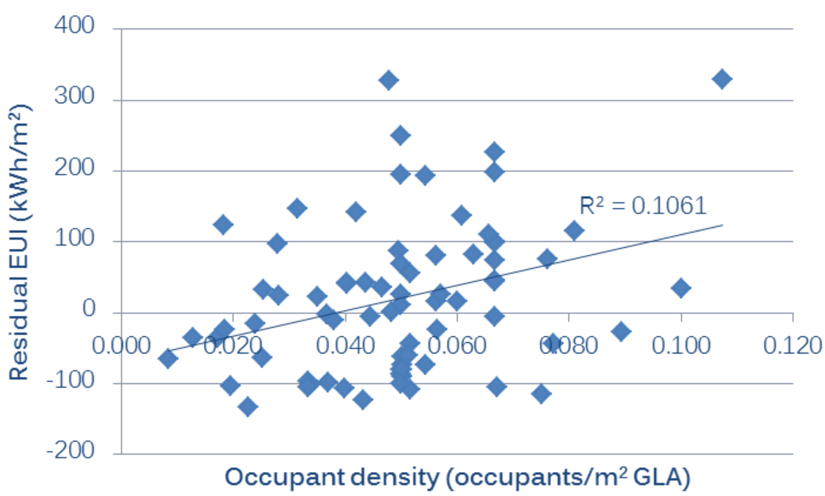


Figure 30: Correlation between occupant density and residual EUI

The residual EUI distribution observed in Figure 30 resembles that of Figure 28 relating to computer density. This is further evidence that the two variables are closely related. Nevertheless, based on ease of measurement and auditing, computer density should be used in favour of occupant density.

4.2.5 Lettable office space (% of GLA)

As the full sample data is mostly limited to GLA, the area data often includes non-office spaces such as retail and common areas (e.g. foyers/lobbies). If there are considerable differences in energy use intensity between different space types, there should be a noticeable correlation between % lettable office space and EUI.

Of the 83 sites in the detailed subset, 68 sites were able to provide the size of the building office space in m^2; the responses are presented in Figure 31 below.

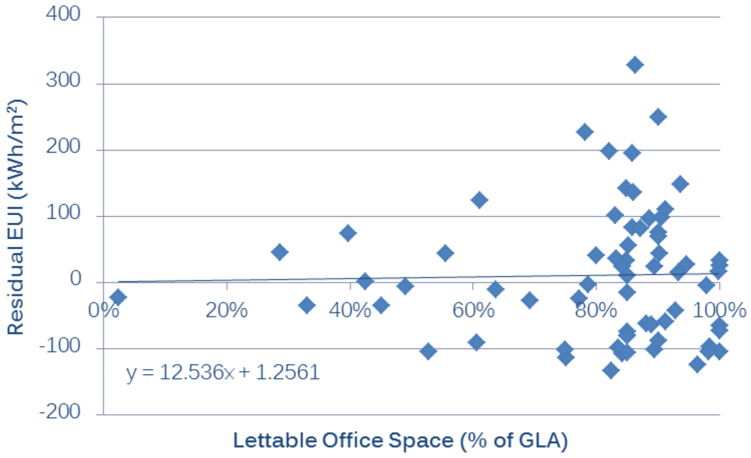


Figure 31: Correlation between Lettable Office Space (% of GLA) and residual EUI

There is no observable trend in Figure 31 for the residual EUI when compared against % of Lettable Office Space and this is sufficient evidence to rule out an empirical correction for the proportion of office space. What this plot also suggests is that in commercial buildings, non-office spaces such as retail do not necessary consume more or less energy per square meter than standard office spaces.

4.2.6 Vacancy rate (% of GLA)

A vacancy rate could be incorporated into the model as current total GLA figures are unadjusted for vacancy. While vacant spaces count towards the total GLA of a building, they do not support any occupants and should therefore consume little or no energy.

Of the 83 sites in the detailed subset, 63 sites were able to provide information on average vacancy rate throughout the year; the responses are presented in Figure 32 below.

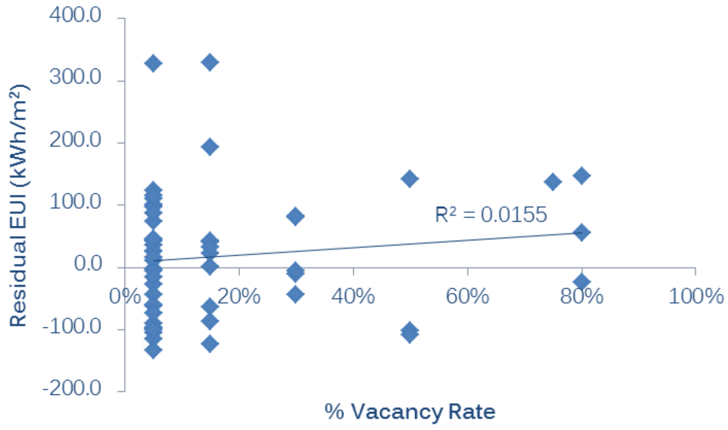


Figure 32: Correlation between building vacancy rate and residual EUI

Ideally, vacant and unoccupied spaces do not require normal building services, this should lead to reduced energy consumption. However, in Exergy's auditing experience, many office building HVAC systems are unable turn down services to vacant spaces and this is the most likely explanation for the weak and counterintuitive trend in Figure 32 which shows building EUI increasing with vacancy rate. The possibility also exists that a number of survey respondents misinterpreted the query and instead specified the occupancy rate; this is a distinct possibility for buildings that are reporting over 50% vacancy. To address this, the same correlation is examined after excluding the potential outliers and the resultant Figure 33 shows vacancy effects on water use is negligible.

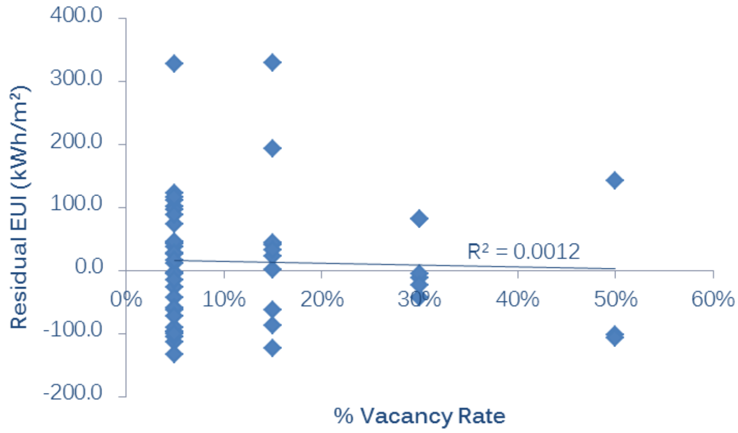


Figure 33: Correlation between building vacancy rate and residual EUI (excluding potential outliers)

While there is insufficient empirical evidence to justify a benchmark correction, from a policy perspective, it is highly recommended that GLA assessments in-tool exclude vacant spaces to encourage HVAC turn down and energy savings.

4.2.7 Car park density (car parks per m^2 GLA)

Only some buildings provide car parking to its tenants or to the public. Under other ratings tools, such as NABERS in Australia, energy use of public car parks (i.e. not limited to tenants) is excludable from assessable energy consumption; energy use of car parks dedicated to tenant use is considered a building service and included in assessable energy consumption. It is important in this instance to see if availability of car parks actually results in higher EUI for the South African data set.

Of the 83 sites in the detailed subset, 59 sites were able to provide information on car park density and whole building energy consumption including car park services; the responses are presented in Figure 34 below.

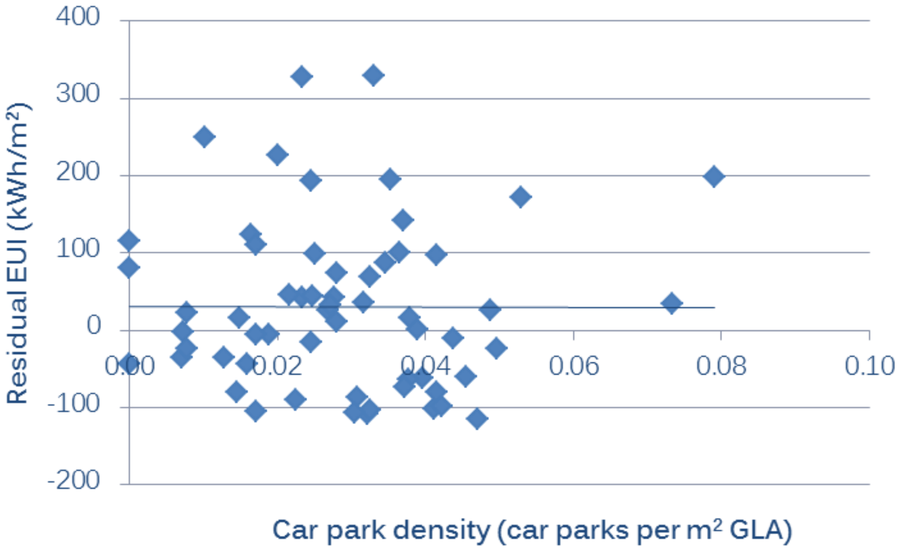


Figure 34: Correlation between car park density and residual EUI

When compared to whole building EUI, the impact of car park energy consumption appears to be minimal. Based on the trend above (or lack thereof), there is no empirical evidence to support a residual correction based on car park density.

4.2.8 Conclusion

This section sought to identify any underlying relationships between building energy performance (residual EUI) and a number of potential consumption drivers. Based on observed linear correlations and the strength of such correlations, the most significant driver of building EUI is the computer density and occupant density metrics. While more data is available at this time on occupant density, it is much harder to audit under an assessment framework, for this reason, the computer density metric should be favoured in the subsequent regression analysis.

4.3 Occupancy-hours Correction through Building Simulation

As discussed previously in Section 4.2.2, there are both theoretical and simulated evidence that building occupancy hours directly affects energy consumption and EUI. This section of the report will present the simulation results supporting an operating-hours correction for building energy.

4.3.1 Model Description

To estimate the impact of longer occupancy-hours on whole building energy consumption, Aurecon carried out detailed analysis with IES which simulated whole office building energy consumption in 2 different locations (Cape Town, Johannesburg) and under 9 occupancy scenarios. The 9 simulated occupancy scenarios were:

- 50 hours per week (5 work days, no after hours)
- 75 hours per week (5 work days, full occupancy after hours)
- 70 hours per week (7 work days, full occupancy after hours)

- 120 hours per week (6 work days, full occupancy after hours)
- 168 hours per week (24/7 operation, full occupancy after hours)
- 75 hours per week (5 work days, half occupancy after hours)
- 70 hours per week (7 work days, half occupancy after hours)
- 120 hours per week (6 work days, half occupancy after hours)
- 168 hours per week (24/7, half occupancy after hours)

The simulations were performed in accordance with the GBCSA modelling protocol for a notional building. The only variation from the protocol was that the HVAC system had a supply temperature reset strategy, as opposed to a constant 12°C supply air temperature. The model geometry was the same as that used for the Aurecon Pretoria GBCSA Green Star Submission (Notional Building), where the building achieved 4 stars. The building is a 6 storey office block with 4 levels of basement parking. The model was assigned default SANS 204 constructions and glazing areas, no shading was included. The HVAC system was modelled as a chilled water variable air volume system with terminal reheat and supply air temperature reset. The model had a constant volume chilled water system with air cooled chillers.

Other key input parameters for the simulations are as follows:

Building Inputs (Johannesburg and Cape Town)	
Total Gross Floor Area (GFA) in m²	22056.75
Total Commercial Office GFA in m²	16747.45
Total Commercial Office Usable Area (UA) in m²	16747.45
Total Car Parking Area in m²	26422.10
Sub basement Parking Area (B2 and below) in m²	21487.50
External Areas (excluding Car Parking) in m²	2515.30
Internal Gains	
Tenant Lighting Usage (Notional W/m^2)	12
Tenant Small Power Usage (Notional and Actual W/m^2)	11
Occupancy (Notional and Actual m^2/person)	15

Table 9: Key simulation input parameters

4.3.2 Simulation Results

The base line scenario has been selected as a notional 50 hours per week with 5 work days a week and no after-hours occupancy. The simulated building energy consumption for all other scenarios has been presented as a ratio of the base line consumption in Figure 35 and Figure 36 below, i.e. observed ratio = (building consumption with "*x*" occupancy hours) / (building consumption with base case 50 hours of occupancy).

Note that hours of half occupancy (during after-hours) have been treated without adjustments as if they were full occupancy.

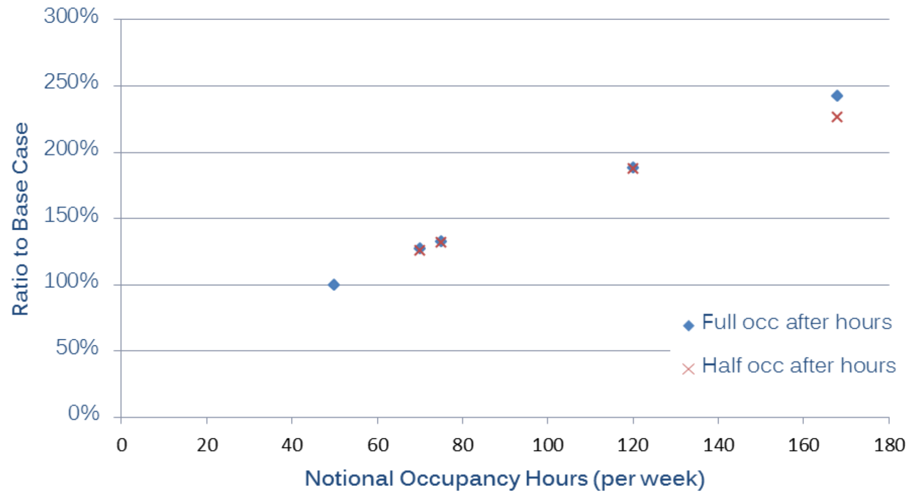


Figure 35: Johannesburg occupancy simulation consumption ratios by operating hours

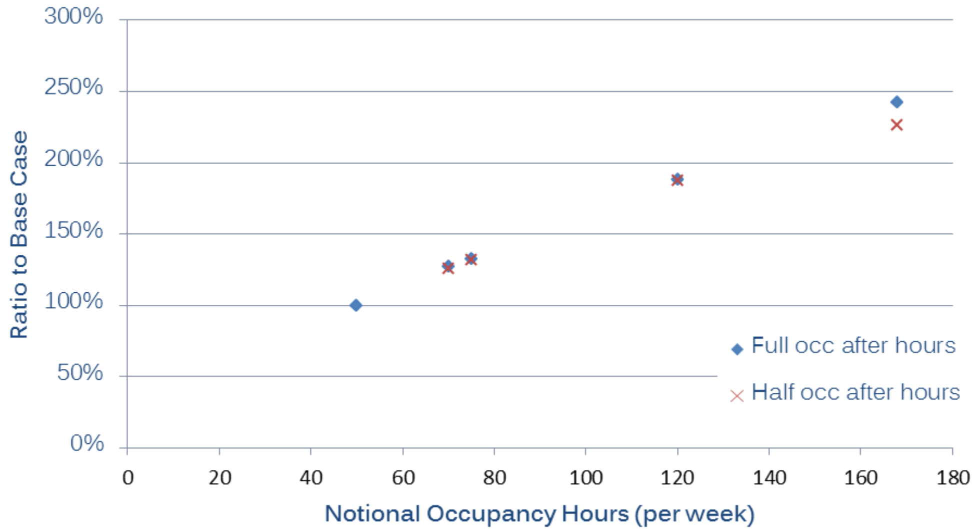


Figure 36: Cape Town occupancy simulation consumption ratios by operating hours

The figures above indicate that occupancy-hours directly influences whole building energy consumption while building location makes no discernible difference. The scale (slope) of the linear correlation suggests that the impact of longer occupancy hours is significant and can be accounted for with a high level of theoretical confidence.

Based on data of Australian office buildings, the average occupancy-hours for rated whole buildings is 45.9 hours per week (5 work days). Therefore, the simulation data was recalibrated with the new base line occupancy of 45.9 hours per week (see Figure 37 below) and the correlation evaluated by linear regression.

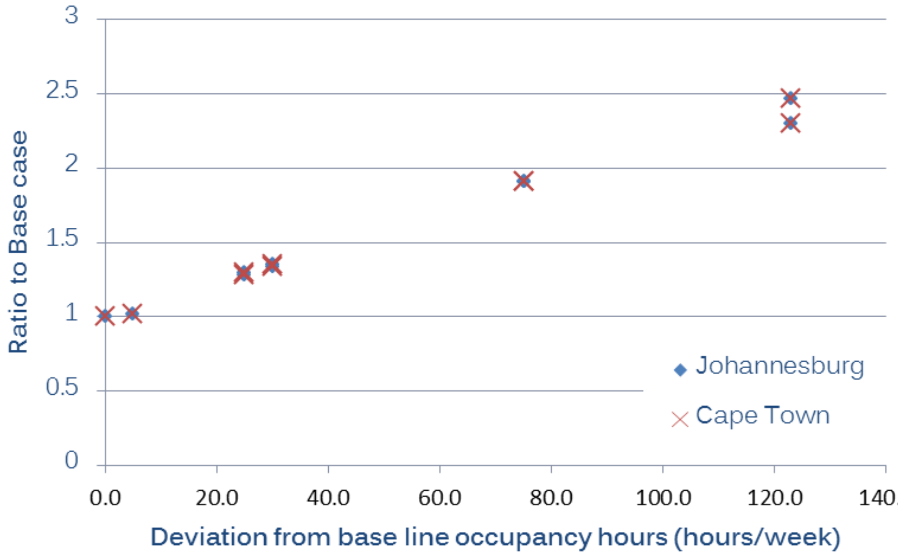


Figure 37: Revised occupancy base line (45 hours)

The model predicted theoretical corrections for occupancy-hours are:

Location	Intercept (%)	Slope (% per hour)
Johannesburg	100%	1.14
Cape Town	100%	1.14

Table 10: Simulation predicted occupancy-hours correction for whole building energy consumption

The simulation outcomes presented in Table 10 estimate that the impact of longer occupancy hours is linear and that the scale of the influence is approximately 1.14% per hour; i.e. if a whole building operates on average 10 hours per week more than another identical building, then it is expected to consume 10×1.14% = 11.4% more energy per annum. As the hours of occupancy approaches 0 (unoccupied), the model predicts that the building base line energy consumption would be 42.5% of the same building operating at 45-hours per week.

It was also important to assess whether a change in building location, and the associated change in climate, would affect the proposed correction. For this reason, occupancy simulation of identical buildings was carried out for both Cape Town and Johannesburg, which fall into distinctly different climate zones. As evidenced by results in Table 10 however, the resulting occupancy-hours corrections were identical for both locations.

4.3.3 Theoretical vs. Empirical Correction

The scale of the theoretical correction for occupancy-hours is compared to the empirical correlation observed for the sample data in Figure 38 below; note that the two potential outliers with 107 and 168 hours per week operations have been excluded to improve the relevance of the comparison (and remove the effects of the influential points that could be potential outliers).

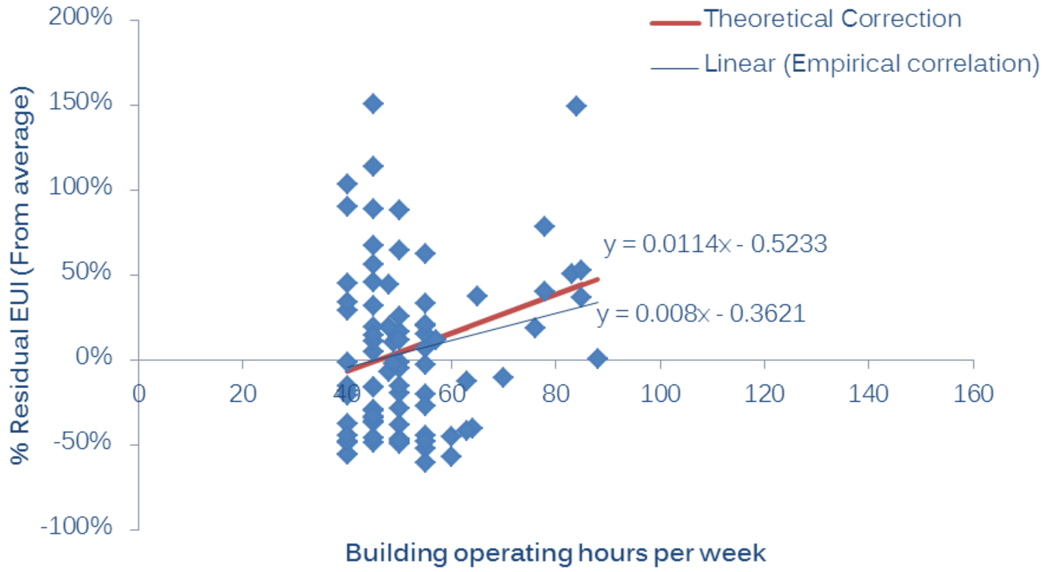


Figure 38: Scale of occupancy-hours theoretical correction vs. empirical correlation

Some conclusion may be drawn through this comparison and some additional analysis:

- The statistical significance of the empirical correlation is poor (as identified previously in Section 4.2.2)
- The scale of the theoretical correction is within reasonable bounds, especially when the noise of the underlying data is taken into consideration

4.3.4 After-hours Occupancy

To characterise the potential effects of reduced occupancy during after-hours, simulations were carried out for both full and half occupancy (after-hours) scenarios. With the exception of the 24/7 buildings, results presented in Figure 35 and Figure 36 show negligible differences in building energy consumption with reduced after-hours occupancy. There is therefore insufficient empirical justification to account hours of reduced occupancy differently to full occupancy. Certainly a threshold should be established below which the building is to be considered unoccupied - 20% is recommended for the South African rating tool, which lines up with similar uproaches on some international tools.

4.4 Climate Correction Through Building Simulation

In the absence of meaningful empirical correlation between sample building efficiency and climate (CDD or HDD), an alternative methodology based on building simulations has been adopted to estimate the impact of climate on building energy efficiency.

Building simulations were conducted in IES for an identical building model (see Section 4.3.1) in a number of climatically diverse locations. The climate simulations assumed the same standard VAV office building as per the occupancy hours simulations with model parameters summarised in Table 9; with all other building parameters kept constant (e.g. run hours, occupant density, equipment density etc.), variations in simulated energy consumption can be attributed to climate effects. To expand the range of simulated climates, five major Australian cities have been added to the two South African cities with reliable EnergyPlus weather files.

Figure 39, Figure 40 and Figure 41 below compare the simulated EUI of the different locations against CDD (base 15˚C WB), HDD (base 18˚C dry bulb) and CDD+HDD.

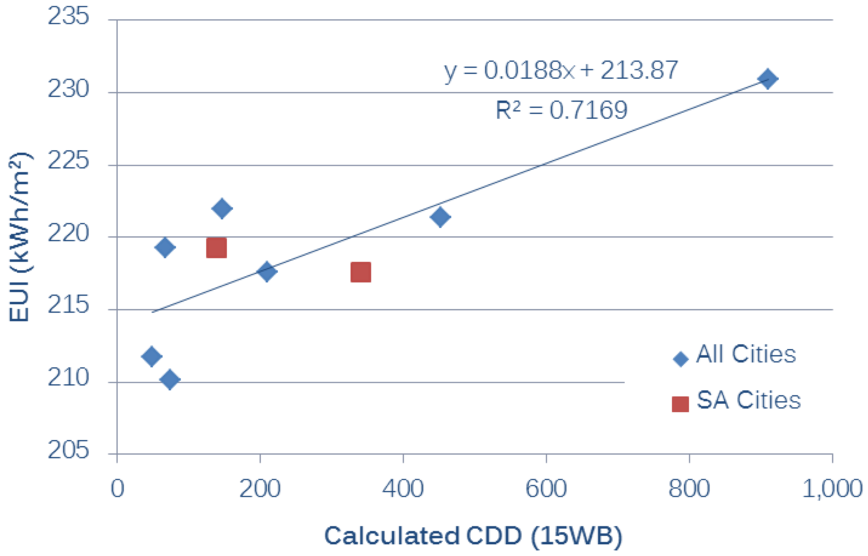


Figure 39: Simulation residuals correlated with CDD (15WB)

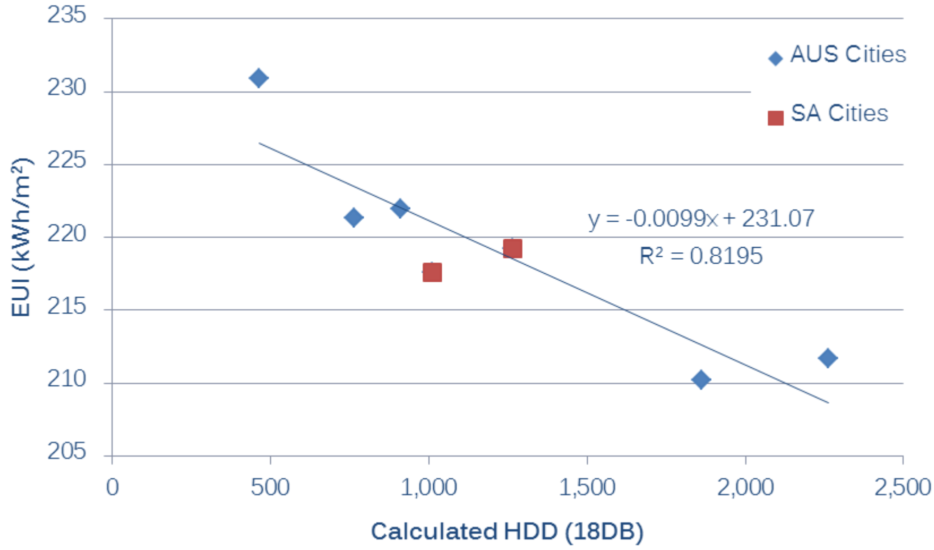


Figure 40: Simulation residuals correlated against HDD (18DB)

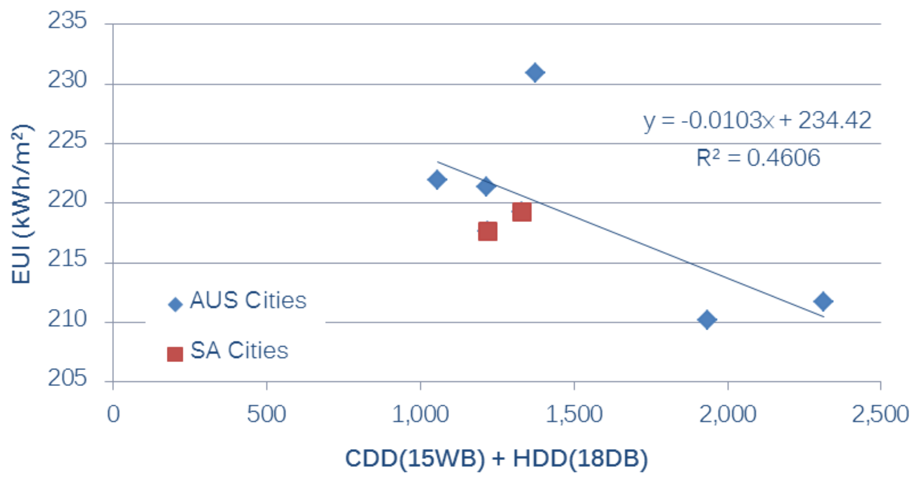


Figure 41: Simulation residuals correlated against CDD (14WB) + HDD (18DB)

While the high correlation coefficients (R^2) in the first two figures suggest that climate has a statistically justifiable impact on EUI, there are two issues to consider when choosing the appropriate climate metric:

- Reliable interval data on wet-bulb temperatures (and therefore CDD) is prohibitively expensive.
- Although HDD produces a strong correlation, the negative slope in Figure 40 (HDD vs. EUI) indicates that it is only a proxy for the cooling demand driving the climate correlation. While more direct metrics for cooling demands are available, HDD should not be favoured in corrections for cooling dominated climate impacts.

To resolve this issue, Aurecon has provided average wet-bulb temperatures at 3 different time-of-day for a comprehensive list of sites (e.g. monthly average wet bulb temperatures at 8am, 2pm and 8pm for over 100 locations). Based on further analysis, it is possible to correlate building EUI with annual average wet bulb temperature to obtain a climate correction. The relationship between annual average wet bulb temperature and simulated building EUI is illustrated in Figure 42 below.

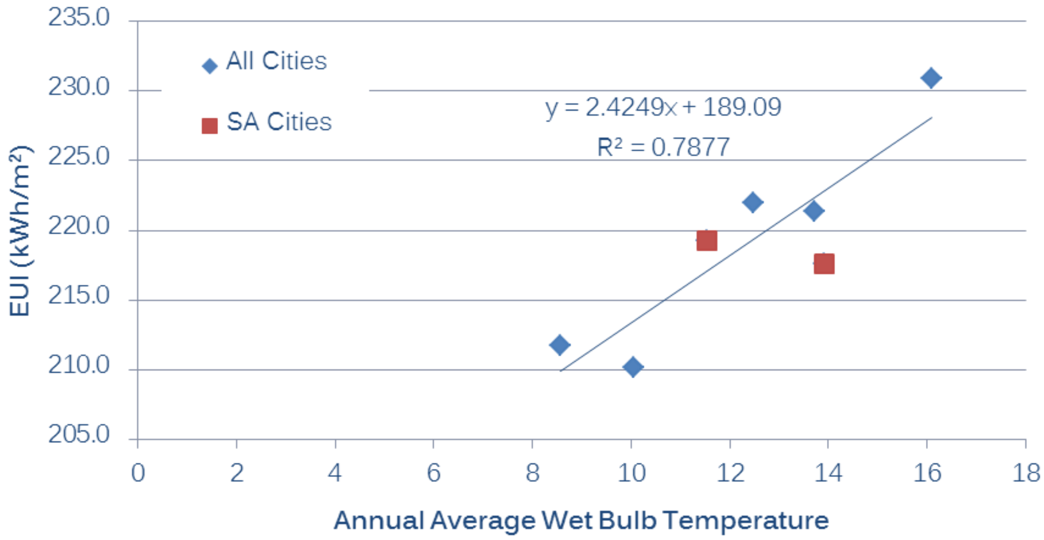


Figure 42: Relationship between annual average wet bulb temperature and annual CDD (base 15wb)

Combining the temperature data and geographical/postal information provided by Aurecon, Exergy has developed a list of postcode lookups to provide annual average wet bulb temperatures for all locations throughout South Africa.

Linear regression was used to quantify the relationship between annual average wet bulb temperatures (above and below the sample average wet bulb temperature) and simulated building EUI. The regression output is presented below in Table 11.

Regression Statistics	
R^2	0.788
Model Significance	0.00766
Observations	7

	Coefficients	*Standard Error*	*P-value*
Intercept	219	1.32	1.54E-10

avg Twb	2.42	0.563	0.00766

Table 11:Regression output for climate correction with average wet bulb temperature

The regression output indicates that the (absolute) climate impact on building EUI is approximately 2.42kWh/m^2/year per ˚C above or below the sample mean annual wet bulb temperature (12.3˚C). The benchmark (predicted) energy consumption for a building is therefore corrected by the following formula:

$$Climate\ Correction\ (kWh/m^2) = 2.42 \times (Annual\ \ T_{avg_{WB}} - Average\ T_{avg\_wb})$$

Where the average T is the sample average annual wet bulb tempeature of the 7 climate zones used to evaluate the correction factor; which is 12.3˚C. Therefore,

$$Climate\ Correction = 2.42 \times (Annual\ \ T_{avg_{WB}} - 12.3)$$ **Equation 4**

4.5 Energy Benchmark Model

From Equation 1, we have

$$Actual\ EUI = Expected\ EUI + \varepsilon$$

Where the Expected EUI is the full sample average EUI, 219 kWh/m^2.

Residual analysis carried out in the preceding sections identified that computer density can be used to explain a portion of the variability in ε. Linear regression will be utilised in this section to quantify the impact of computer density and construct the final benchmark model.

4.5.1 Linear regression model

The relationship between residual EUI and computer density may be described by the following simple linear regression model:

$$\varepsilon\ = \beta_0 + \beta_{comp} \times Computer\_Density\ + \ \delta$$ **Equation 5**

Where β_0 and β_{comp} are the regression coefficients evaluated via least squares linear regression modelling; δ is the residual term that includes the portion of the variation in residual EUI that cannot be explained by computer density.

Analysing the data via a statistics package provides the following output for Equation 5:

Regression Statistics	
Mode Significance F	0.0336
R Square	0.0839
Observations	54

	Coefficients	*Standard Error*	*P-value*
Intercept	-46.0	32.3	0.161
Computer Density	1440	658	0.0336

Table 12: Regression output for computer density correction

The coefficients in Table 12 quantify the relationship between computer density and residual EUI, suggesting a benchmark model of the following form:

$$Predicted\ EUI\ = 219 + (\beta_0 + \beta_{comp}\ \times\ Computer\_Density\ )$$

$$Predicted\ EUI\ = 219 + (-46.0\ +\ 1440 \times Computer\_Density)$$

$$\boldsymbol{Predicted\ EUI\ = 173 + 1440 \times Computer\ \ Density}$$

Equation 6

Equation 6 above evaluates the predicted EUI for an office building when the computer density (computers/m^2) is known; the predicted EUI is essentially the market average EUI for a building with the given characteristics.

Other key indicators in Table 9 provide model diagnostics and statistical support for the significance of the relationship, namely:

- The regression R^2 coefficient of 0.08 indicates that 8% of variation in residual EUI can be explained by computer density.
- The model significance is acceptable, suggesting that there is better than 97% confidence in the significance of the relationship (higher than 97% certainty that there exists a relationship between residual EUI and computer density).
- The p-value for the coefficient β_{comp} is low. This is a strong indication of coefficient significance (i.e. there is more than 97% confidence that the relationship is non-zero).

Note that although computer density only explains 8.3% of variation in residual EUI, a majority of the variation in building energy consumption has already been accounted for by building size. Combined, the model is able to explain approximately 90% of variation in whole building energy consumption.

4.5.2 Adjusting the Model for Occupancy Hours

To include the theoretical occupancy-hours correction evaluated in Section 4.3, Equation 6 which estimates average energy consumption for a given building at standard (unspecified) occupancy-hours, will need to be adjusted by the coefficients presented in Table 10. Adjusting for occupancy-hours yields the following model:

$$\boldsymbol{Predicted\ EUI\ = (173 + 1440 \times Computer\ \ Density) \times [1 + 0.0114 \times (Occupancy\ Hours - 45.9)]}$$

Equation 7

4.5.3 Adjusting the Model for Climate

To include the simulation derived climate correction evaluated in Section 4.4, Equation 7 will need to be further adjusted by the formula described in Equation 4. Adjusting for climate yields the following model:

$$\boldsymbol{Predicted\ EUI\ = (173 + 1440 \times Computer\ \ Density) \times [1 + 0.0114 \times (Occupancy\ Hours - 45.9)] + 2.42 \times \left(Annual\ T_{avg\_wb} - 12.3\right)}$$

Equation 8

4.5.4 Converting to Predicted Median Consumption

Combining all corrections, the predicted average EUI of an office building is expressed as per Equation 8 above. This is then multiplied by the building size (GLA) to obtain an estimate for the mean (expected) building energy consumption in kWh:

$$\begin{aligned}\boldsymbol{Predicted\ kWh} &= \{(\mathbf{173} + \mathbf{1440} \times \boldsymbol{Computer\ \ Density}) \\ &\quad \times [\mathbf{1} + \mathbf{0.0114} \times (\boldsymbol{Occupancy\ Hours} - \mathbf{45.9})] \\ &\quad + \mathbf{2.42} \times (\boldsymbol{Annual\ T_{avg\_wb}} - \mathbf{12.3})\} \times \boldsymbol{GLA}\end{aligned}$$

Equation 9

Before utilising the benchmark model as part of an energy rating tool, it is necessary to adjust the model predicted kWh from an estimated <u>mean</u> to an estimated <u>median</u>. The use of medians is essential in the context of a rating tool based on relative building performances, as averages may be substantially skewed by outliers and extreme values. Since the distribution of office building EUI is positively skewed (as there is often no upper limit for how inefficient a building can be, see Figure 7), the median building EUI is a more accurate representation for the "middle" efficiency level.

To convert predicted average consumption to predicted median consumption, the predicted consumption in Equation 9 needs to be adjusted by the median residual value of -11.2% (based on the data). Namely,

$$\begin{aligned}\boldsymbol{Predicted\ kWh} &= \{(\mathbf{173} + \mathbf{1440} \times \boldsymbol{Computer\ \ Density}) \\ &\quad \times [\mathbf{1} + \mathbf{0.0114} \times (\boldsymbol{Occupancy\ Hours} - \mathbf{45.9})] \\ &\quad + \mathbf{2.42} \times (\boldsymbol{Annual\ T_{avg\_wb}} - \mathbf{12.3})\} \times \boldsymbol{GLA} \times \mathbf{0.882}\end{aligned}$$

Equation 10

4.5.5 Final Energy Model

As per Equation 10, Figure 43 below compares reported actual MWh (1,000 kWh) against the model predicted MWh.

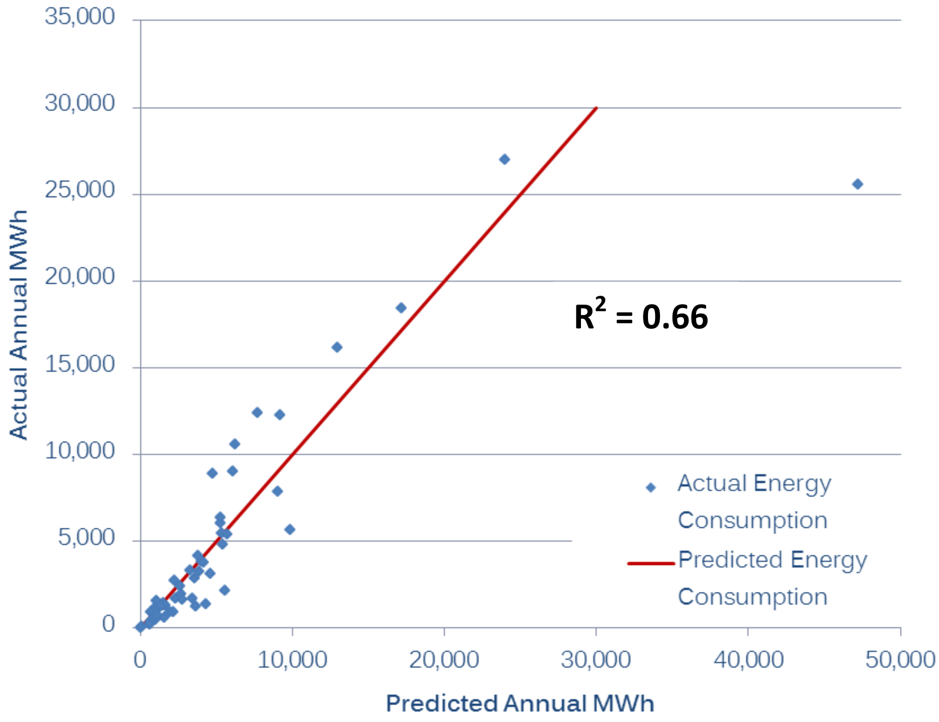


Figure 43: Benchmark model predicted MWh vs. actual MWh

There is a generally good fit throughout the range of sites in the detailed data subset with the exception of a single potential outlier. Further investigation revealed that the unusual site reported very long hours of operation but lower than expected energy consumption; the model significance improves substantially when this site is excluded.

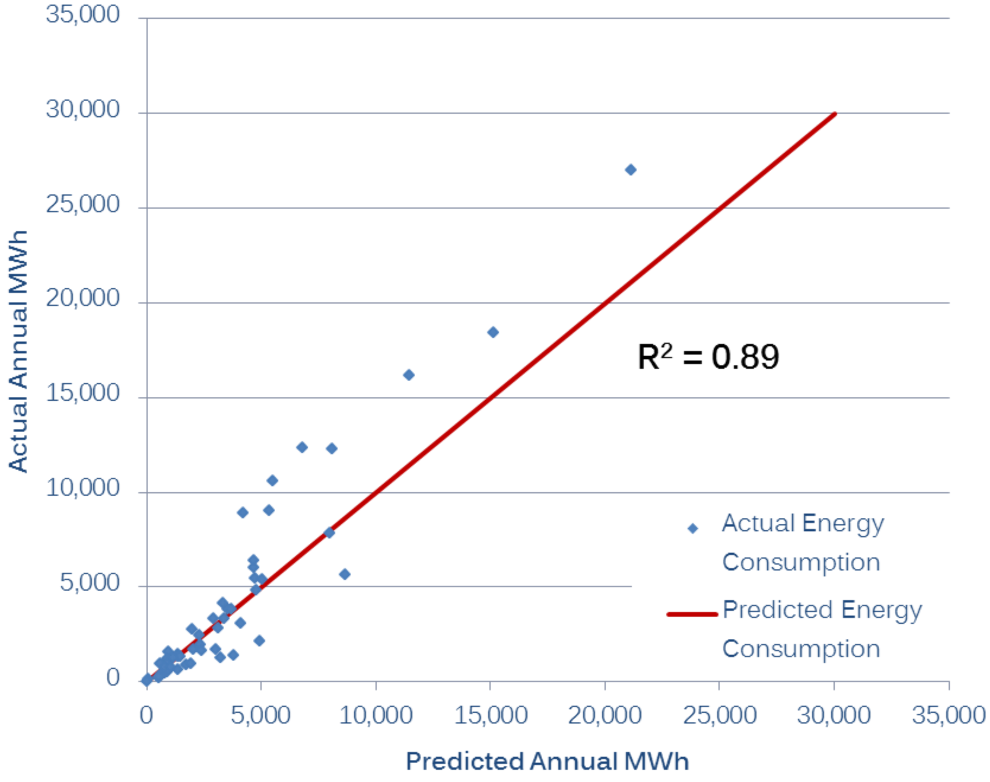


Figure 44: Benchmark predicted MWh vs. actual measured MWh.

As Figure 44 illustrates, the exclusion of the potential outlier can significantly improve the strength of the correlation (from R^2=0.66 to R^2=0.89).

4.6 Residual Analysis – Energy Benchmark

The preceding sections provided justification and evaluation of several correction factors for inclusion in the energy benchmark model. However, further analysis of residuals is required to determine whether any inherent biases exist in the model output. Model bias usually indicates one of two things: second-order relationship(s) that require further correction or over compensation of theoretical correction(s).

Residual analysis through graphical and regression analysis was conducted for a number of key parameters to examine whether there are any underlying bias issues. Table 13 below presents a summary for both the correlation coefficient (R^2) and statistical significance (p-value) evaluated for each factor's correlation against model % residuals. Strong correlation is usually signified by R2 in excess of 0.1 (at least 10% of variation in % residuals could be explained by the factor) and high statistical significance is usually signified by p-values less than 0.05 (95% confidence that a non-zero correlation exists).

Factor	R2	p-value
Fitted values (kWh consumption)	0.058	0.68
Building Size (m^2 GLA)	0.03	0.21
Computer Density (computers/m^2)	0.0072	0.54

Occupant Density (occupants/m^2)	0.0036	0.68
Occupancy-Hours (hours/week)[1]	0.05	0.1
Climate (average annual WB ˚C)	0.029	0.22
Car park density (parks/m^2)	0.032	0.23
% Active Cooling	0.0093	0.5

Table 13: Residual analysis summary for energy model % residual output

As the table demonstrates, in all cases tested, the statistical significance of the correlation with the model % residual was low. On this basis, it is reasonable to conclude that the benchmark model does not suffer from any underlying bias.

The graphical plots of % residual values against each factor above can be found in Appendix A.

4.7 Recommended Rating Bands

The energy benchmark has been shown to provide unbiased predictions of median energy consumption for whole office buildings with the given characteristics data. The energy rating of an individual building is determined by the difference between the building's actual energy consumption relative to the model predicted median energy consumption. The percentage residuals of the model ρ are calculated as:

$$\rho = \frac{E_{measured} - E_{median}}{E_{median}}$$ **Equation 11**

Where $E_{measured}$ is the measured energy consumption for the whole office building and E_{median} is the benchmark predicted (median) energy consumption for the building, both expressed in kWh per annum. This represents how far the rated building is from the industry median (the middle of the pack).

The distribution of the residuals ρ is shown in Figure 45 below.

[1] Note that the occupancy-hours correlation to % residuals falls to R2 and p-value of 0.036 and 0.18 respectively when we exclude 1 potential outlier reporting longer than expected hours.

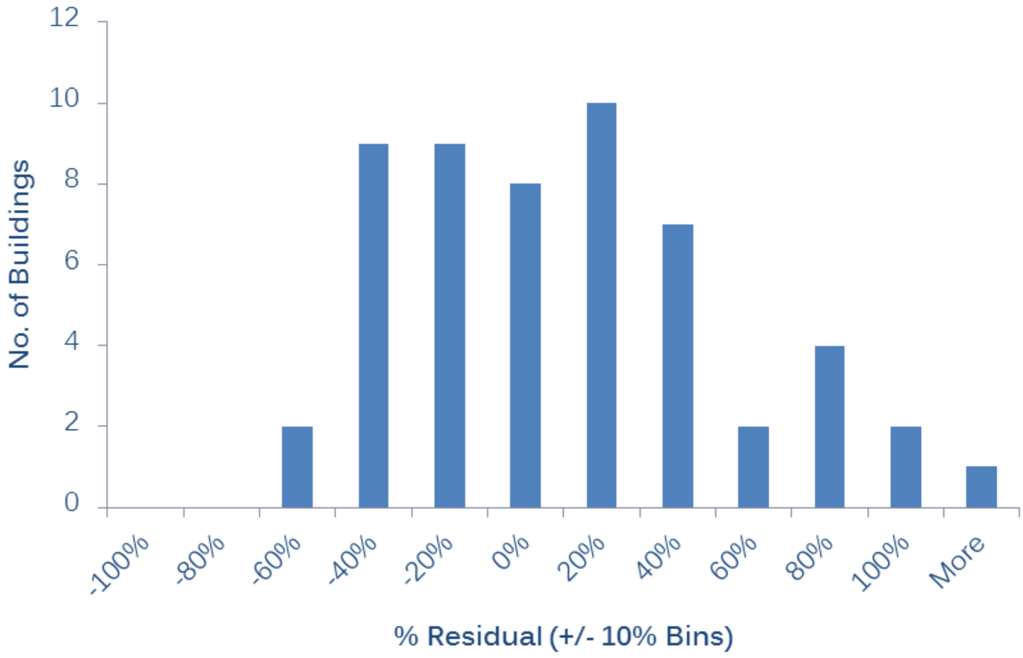


Figure 45: Distribution of benchmark model residuals (±10% on each bin)

To convert this model into a performance rating tool the following approach has been used to set the rating bands based on a 10-point rating scale:

- The site's predicted energy consumption E_{median} is calculated (Equation 15)
- The site's measured energy consumption $E_{measured}$ is obtained (e.g. from utility bills)
- The residual ρ is calculated as described in Equation 11.
- The rating is calculated based on the size of the residual relative to the predicted consumption (percentage residual). The rating equation is based on $R = A - B\rho$ where R is the rating for the building, A is the midpoint of the "median" building's rating band, ρ is the percentage residual and B is the rating band co-efficient.
- The rating value R is rounded down to the nearest integer category;
- The highest rating score is 10;
- The lowest rating score is 1;

The rating band co-efficient B was established on the basis of obtaining a "desirable" distribution of rating outcomes. This was done in such a way that the final rating distribution has the following characteristics:

- The "median" building performance, represented by coefficient A is defined such that the lowest 10 to 20 percentile of buildings receive a rating score of 1 or 2.
- The distribution of ratings is suitable (i.e. not biased towards higher or lower ratings).
- Rating score of 10 is energy neutral (0 net energy intake)
- Linear rating scale between 1 and 10 (e.g. absolute difference in kWh between scores of 2 and 3 the same as difference between scores of 7 and 8).

Based on these criteria, the rating equation has been assessed as:

$$\boldsymbol{R = 5.5 - 4.5\rho}$$ **Equation 12**

The chosen coefficients mean that a building with an "average" level of energy efficiency (industry median) would be rated with a score of 5 (5.5 rounded down). The final rating distribution for the sites used in developing the model is shown in Figure 46 below.

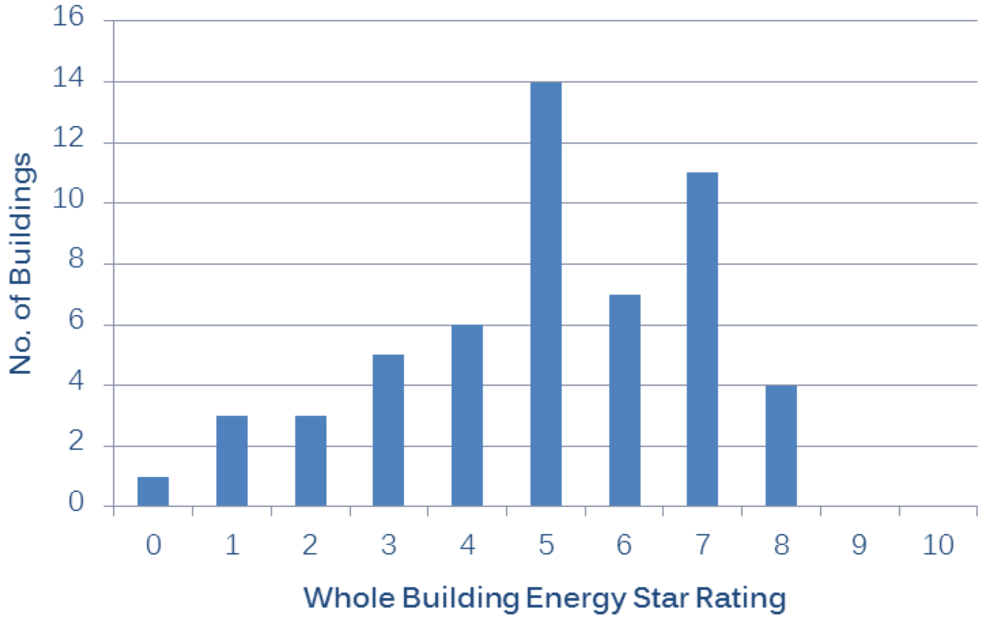


Figure 46: Sample whole office building energy rating distribution

This distribution shows that the rating band coefficients achieve the two objectives of the rating design, being (1) to ensure that most of the office building population is rateable and differentiable; and (2) to set an aspirational performance target for new and existing buildings (score of 8 to 10).

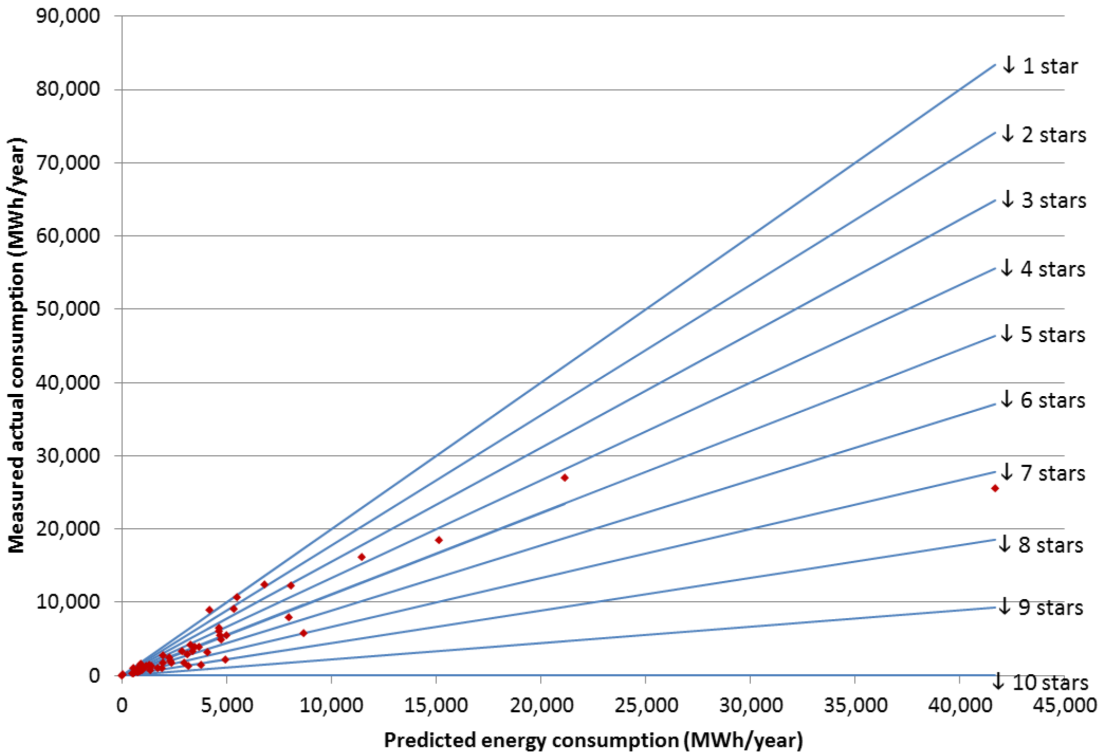


Figure 47: Whole building energy consumption rating bands

The rating bands are a function of all the parameters within the office building – in plain terms, a customised set of rating bands is created for each office building, based upon its area, computer capacity, occupancy-hours and climate. The methodology used ensures that the distribution of sites against each of these variables is independent of these characteristics.

Rating bands are representative of constant increments in energy consumption; i.e. the raw kWh separating a rating score of 1 and 2 for a single site is the same as that separating a rating score of 7 and 8. Each rating band is equivalent to approximately 22% of predicted median consumption. The bands (cut-off for % residuals) are detailed in Table 14 below.

Rating score, at beginning of rating band	Consumption compared to benchmark predicted consumption
10	0%
9	22%
8	44%
7	67%
6	89%
5	111%
4	133%
3	156%
2	178%
1	200%

Table 14: Rating bands relative to median consumption

Note that the middle of the 5.0 rating band (rating score of 5.5) is set to 100% of the predicted emissions (building is performing exactly at industry median efficiency level). While formal rating bands are discrete, the actual underlying decimal rating is a continuous scale from 0 to 10 which is rounded on certification; this is to improve the comparability and ease of interpretation for the building stakeholders.

5 Water Demographic Analysis

The methodology adopted for the water benchmark model will generally follow the process undertaken for the energy benchmark model. Therefore, a large portion of the structure and content in subsequent sections will resemble the demographic and benchmarking analysis already carried out for energy.

While the full sample data set is limited to information on building location, size and climate zone, the detailed subset provides additional demographic information. It is important that analysis is carried out prior to benchmarking to identify underlying trends between demographic factors and building water efficiency as these may distort/mislead regression outcomes (e.g. variation in WUI by building location could be misinterpreted as climate effect). Where a significant relationship is identified, the affected data may need to be excluded from subsequent benchmarking. The list of demographic factors to be examined includes:

- Building location
- Building size
- Year of construction or major refurbishment
- % Active cooling
- Irrigation
- Supply to cooling towers and evaporative coolers

The subsequent sections will analyse each of these demographic variables individually.

5.1 Building Location

The geographic location of the building is directly linked to many intangible social, economic and demographic factors. It is therefore important to examine whether location correlates with WUI in case one or more of these factors influences building water efficiency.

Table 15 presents the mean and median WUI for buildings by their location.

Region	GLA	Annual kL	Mean WUI kL/m^2	Median WUI kL/m^2
Johannesburg	1,232,312	1,096,015	1.10	0.79
Pretoria	481,941	548,717	1.39	1.02
Rest of Gauteng	125,029	167,105	1.46	1.25
Western Cape (incl. Cape Town)	488,108	497,713	1.03	0.92
KwaZulu Natal (incl. Durban)	232,540	291,665	1.20	1.13
Other	131,741	57,198	0.54	0.37
Total	**2,691,671**	**2,658,414**	**1.14**	**0.88**

Table 15: Comparison of mean and median WUI by building location

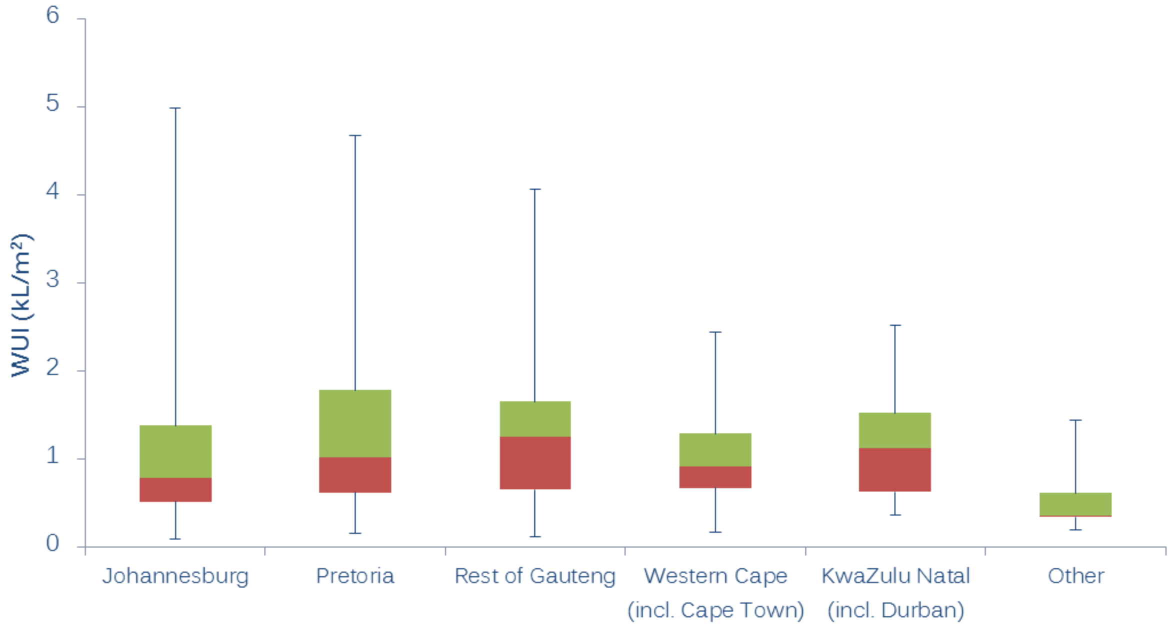


Figure 48: Box whisker plot comparing distribution of WUI by geographic location

Based on data presented in Table 15, the mean and median WUI values appear to vary slightly by location, particularly in "other" regions outside of the major capital cities.

It is difficult to conclude, based on Table 15 and Figure 48 alone, whether the WUI is strongly affected by location as there is a considerable level of data noise/variability. A two tailed t-test was therefore conducted for each regional subset against the full sample data set to quantitatively assess if the variation in mean WUI for any region is statistically significant. Table 16 summarises the outcomes.

	Mean WUI kL/m^2	Probability that subset mean equals population mean (p-value)
Johannesburg	1.10	0.75
Pretoria	1.39	0.14
Rest of Gauteng	1.46	0.54
Western Cape (incl. Cape Town)	1.03	0.26
KwaZulu Natal (incl. Durban)	1.20	0.64
Other	0.54	0.0001

Table 16: Mean WUI by region and t-test for difference of mean from full sample

The results presented in Table 16 suggest that the mean WUI of the "other" regional subset differs significantly from that of the underlying population (0.01% probability that means are equal). Given that the "other" region classification encompasses a diverse range of more remote geographic locations, this discrepancy is unexplainable and could have an undesirable demographic impact on subsequent analysis. Empirically, the subset of "other" regional data should be excluded from analysis to avoid distorting the benchmark (14 sites in total).

5.2 Building Size

The system complexity and level of services provided usually increase with building size, as is the case with the Australian office building stock where larger office buildings are usually "premium" grade to attract higher rental prices. Although the increase in complexity and services may theoretically result in higher WUI, studies to date have not identified a statistically significant link between building size/quality and WUI. Figure 49 below illustrates that the same can be said for the South African office building stock where there is no visible correlation between building size and WUI.

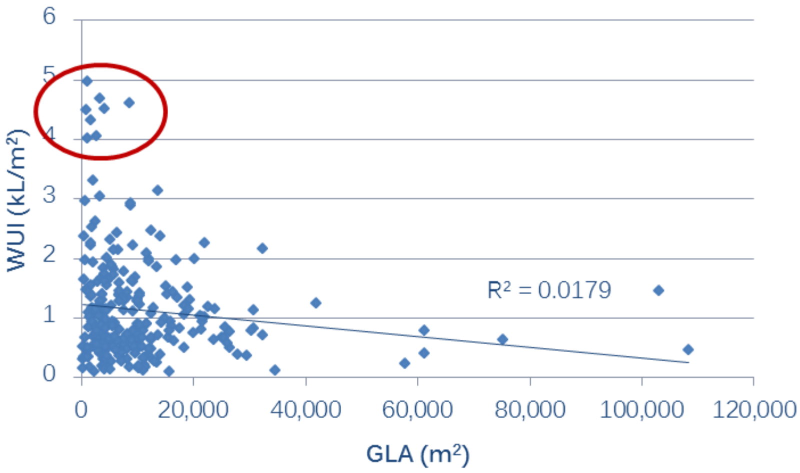


Figure 49: Building size (GLA) vs. WUI

The apparent negative slope of the trend line is entirely driven by the small group of potential outliers with very small floor plates and very high WUI. Based on the weak correlation (R^2=0.0079) between building size and WUI in the remainder of the data (Figure 50 below), it is reasonable to conclude that building size is not a significant contributory factor in building water efficiency. Moreover, the lack of correlation between WUI and building GLA provides assurance that the relationship between GLA and kL is not non-linear.

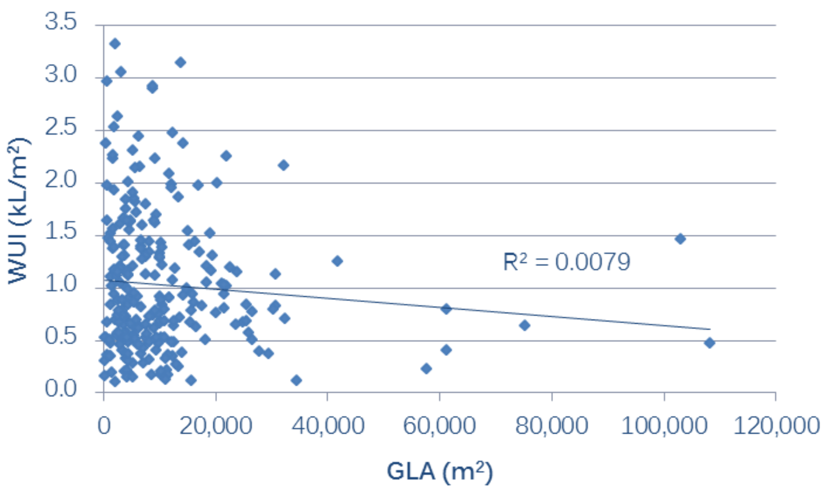


Figure 50: Building size (GLA) vs. WUI excluding outliers

5.3 Year of Construction or Major Refurbishment

Recently constructed or refurbished buildings often promise improved water efficiency but as previously stated, a performance benchmark tool cannot and should not correct for this (i.e. allow older buildings to perform poorer) as it would remove water efficiency incentives in older buildings. Figure 51 below plots the year of construction or last major refurbishment against building WUI.

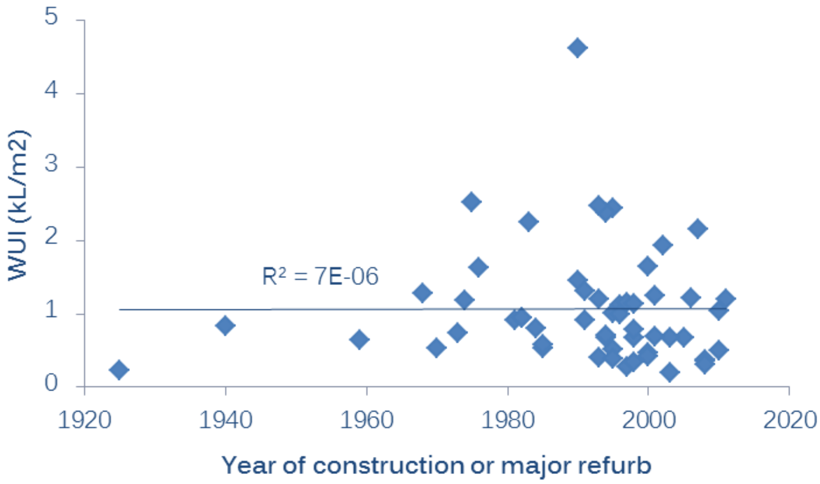


Figure 51: Year of construction or major refurbishment vs. WUI

Figure 51 shows no empirical correlation between year of construction/refurbishment and building WUI (note $R^2 \approx 0$). The year of construction/refurbishment therefore has any no significant impact on building water efficiency.

5.4 % Active Cooling

Building HVAC services vary from natural ventilation only to mechanical air conditioning only and anywhere in between. As part of the questionnaire, respondents were asked to specify the % of total building area covered by the building's active air conditioning system. This information is helpful in identifying atypical buildings within the data (e.g. little or no active cooling) and whether these are likely to cause any discrepancies in subsequent benchmark analysis.

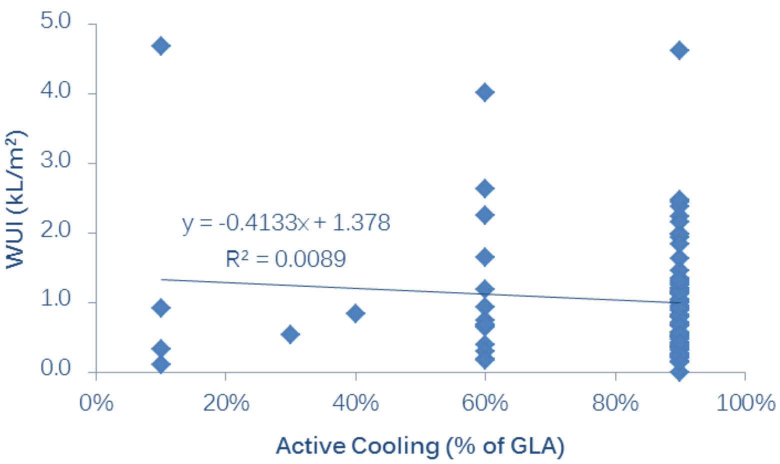


Figure 52: Impact of % active cooling on building WUI

Figure 52 above indicates that the % coverage of active air conditioning makes little difference to building water efficiency. This outcome was unexpected but there are several possible explanations:

- Respondents may have misinterpreted the questionnaire and responded with the % of active A/C provided by the base building (building owner) and neglected to include coverage of tenant installed active A/C units.
- The prevalence of air-cooled systems means water consumption is relatively independent of central HVAC use when examining the sample as a whole.
- Tenant installed equipment and services may be negating any reduction in WUI achieved through natural ventilation and/or passive cooling.
- The buildings with less than 20% active cooling may be outliers. At the very least, the building with 10% active cooling and 4.7kL/m^2 WUI is exerting excessive influence.

It should also be noted that there are very few buildings with less than 50% active cooling so the impact of these buildings on the benchmark model will be minimal. It may be necessary to exclude these sites to avoid distortions to benchmark outcomes.

5.5 Cooling Towers

The questionnaire also asked buildings to indicate whether the base building water consumption covers cooling towers. Cooling towers contribute to a significant portion of a building's water consumption through evaporative and bleed losses; its inclusion is expected to increase WUI substantially. Figure 53 below shows building WUI against supply of cooling towers.

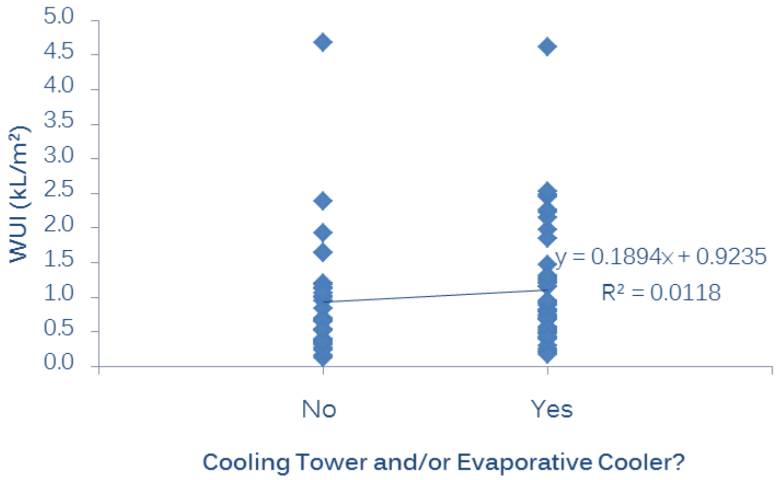


Figure 53: Impact of cooling towers on building WUI

While the qualitative comparison suggests that cooling towers may contribute to a slight rise in average building WUI, an empirical t-test was carried out to quantify the significance of the difference. Results are presented in Table 17 below.

	No Cooling Towers or Evap Coolers kL/m^2	*Cooling Towers or Evap coolers kL/m^2*
Mean	1.02	1.11
Variance	0.96	0.76
Observations	41	43
Hypothesized Mean Difference	0	

t Stat	1.99
P(T<=t) two-tail	0.65

Table 17: two tailed t-test for difference in means between WUI of buildings with and without cooling towers

Based on the outcomes of the t-test, there is no significant difference in average WUI between buildings with and without cooling tower water consumption. This outcome is unexpected and indicates that the water consumption of the sample buildings may not be driven by HVAC consumption. For this reason, the effect of irrigation on water use is also investigated in Section 6.2.8.

5.6 Analysis with Full Data Set vs. Detailed Subset

The set of building data used for water benchmarking is virtually identical to the set used for energy benchmarking. For this reason, analysis carried out previously in Section 3.6 can be utilised to justify that the detailed subset is a representative and unbiased sample of the full data set. A similar analysis to that carried out in Section 3.6.3 can be used to compare detailed subset WUI distribution against the full sample WUI distribution. Figure 54 below qualitatively compares the two distributions.

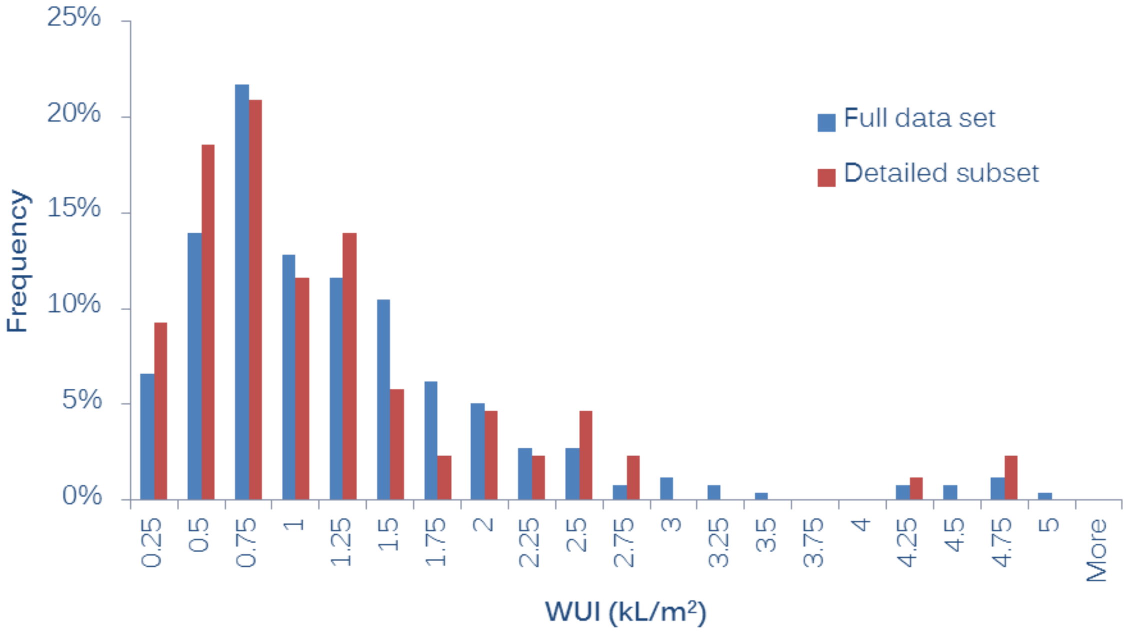


Figure 54: Full data set vs. detailed subset – comparison of WUI distributions

The figure does not suggest that there is a significant difference in WUI distribution between the full data set and detailed subset. Statistical t-test should provide further quantitative confirmation.

	Full data set kL/m^2	*Detailed subset* kL/m^2
Mean	1.14	1.07
Variance	0.78	0.85
Observations	256	84
Hypothesized Mean Difference	0	
t Stat	1.98	
P(T<=t) two-tail	0.551	

Table 18: two tailed t-test output for mean WUI of full data set vs. mean WUI of detailed subset

The high probability (~0.55) suggests that the null hypothesis cannot be rejected, i.e. the mean WUI underlying the two data sets are not significantly different.

The outcome of the statistical t-test indicates that the distribution of WUI in the detailed subset is unbiased and adequately representative of the full sample data.

5.7 Conclusion

A number of demographic factors and their impact on building WUI were examined in the preceding sections. The results of the empirical analysis show that variations in sample building WUI was subject to the influence of building location, more specifically those buildings outside of the major cities that fall under the “other” category. Based on the unexplained and significant difference in water consumption, it would be prudent to exclude these sites from further analysis to avoid unnecessary distortions to the benchmark model.

A similar set of conclusions have been drawn here as per Section 3.6 since the data underlying the water benchmark is virtually identical to data underlying the energy benchmark. There is sufficient grounds to conclude that inferences made based on the detailed subset is reasonably representative of the broader sample and population of office buildings in South Africa. While there is a slight sampling bias towards larger buildings, subsequent residual analysis based on the detailed subset is expected to yield unbiased estimates for the relationships between key variables and WUI.

6 Water Benchmarking Methodology

The purpose of the benchmark model is to compare water consumption of office buildings with different characteristics. Using a few input parameters that characterise a building’s physical and operational characteristics, the benchmark model aims to predict the expected (population average) water consumption for a building with the given attributes.

In constructing the benchmark model, the key objective is to explain the variability in building water usage data using a number of key consumption drivers derivable from building characteristics data. Potential consumption drivers are selected from a list of variables underlying the basic and detailed sample data including size, climate, operating hours etc.

6.1 Correcting Water Consumption for Building size

Similar to the justifications used for the energy benchmark model, the water consumption should also be normalised for size as the observed noise in WUI is proportional with building size. Figure 55 illustrates the significant fan-shape distribution observed for raw kL water consumption, i.e. increasing variance with building size.

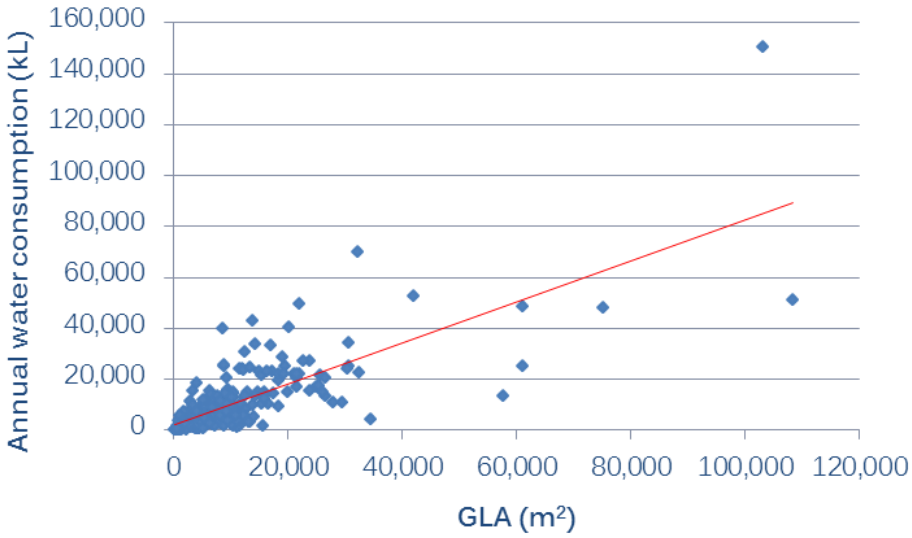


Figure 55: Building annual kL water consumption distributed by GLA (m^2)

As per the energy benchmark, the annual water consumption can be normalised for building size to remove this size correlation, i.e. work with WUI (kL/m^2). In this instance, the expected WUI for a building is the sample average WUI in kL/m^2; the expected annual water consumption is determinable by multiplying with GLA.

Figure 56 below demonstrates the lack of correlation between building size and the normalised water consumption, WUI.

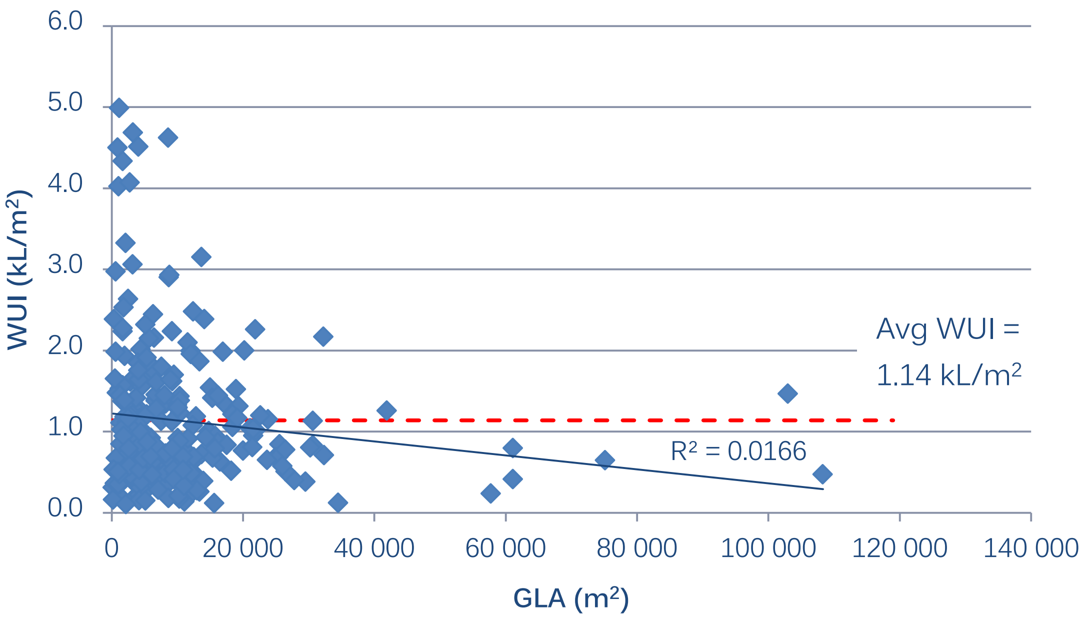


Figure 56: Building WUI distributed by building size (GLA)

The figure above also shows that under the normalised water use approach, the larger buildings in the dataset do not exert excessive influence; where the largest sites were previously considered outliers or influential points in Figure 55; once normalised, their WUI are clearly within reasonable range.

Based on the preceding arguments, the primary correction for scale data should be via the use of WUI which is normalised for building size. The first order estimate for the expected WUI of a given building is therefore:

$$Expected\ WUI\ =\ Sample\ Average\ WUI = 1.14\ kL/m^2$$

Furthermore, the first order estimate for the expected water consumption of a given building is:

$$Expected\ Annual\ kL = Expected\ WUI \times GLA = 1.14 \times GLA$$

This is equivalent to drawing a straight horizontal line as shown in Figure 56 at 1.14 kL/m^2. Buildings above this line have higher WUI than average while those below this line have lower WUI than average. The difference between the observed/measured WUI for each building and this average WUI is called the residual. The residual ε relates to actual building water consumption in the following way:

$$Actual\ WUI = Expected\ WUI + \varepsilon\text{ , OR} \qquad \textbf{Equation 13}$$

$$Actual\ Annual\ kL = (Expected\ WUI + \varepsilon) \times GLA$$

Residual analysis is conducted against a range of other potential consumption drivers to identify any underlying trends in the building WUI. Clearly, WUI does not correlate strongly with building size (Figure 56).

6.2 Residual Analysis with Detailed Subset

The objective of the residual analysis is to explain as much of the variation in residual WUI as possible using a number of potential consumption drivers identified in the detailed subset data. Where a significant relationship exists, the relevant consumption driver(s) can be used to further improve model predictions

Carrying on from Equation 13 in Section 6.1, residual WUI, ε is defined as

$$Actual\ WUI = Expected\ WUI + \varepsilon$$

$$\varepsilon = Actual\ WUI - Expected\ WUI$$

The following sections will investigate a list of potential consumption drivers for correlation with residual WUI in a process that seeks to improve benchmark model explanatory power and reduce the uncertain noise term, ε. The list of potential consumption drivers include:

- Climate
- Occupancy hours (hours per week)
- Occupant density (occupants per m^2 GLA)
- Lettable office space (% of GLA)
- Vacancy rate (% of GLA)
- Car park density (car parks per m^2 GLA)
- Irrigation area (% of GLA)

Note that where possible, the variables have been normalised for building size, e.g. occupant density, % lettable office space, % irrigation area etc. This is necessary as residual WUI is already normalised for size.

6.2.1 Climate

The impact of climate on building water consumption warrants detailed analysis and discussion. Unlike the energy model, there is considerable prior empirical evidence to support a climate correction for water. To investigate the empirical impact of climate on water consumption in South African office buildings, metrics for cooling load and heating load of climate zones, i.e. Cooling Degree Days (CDD) and Heating Degree Days (HDD), were compared against building residual WUI for correlation.

As the most significant climate impacts are limited to buildings with water based heat rejection, Exergy have limited the subsequent climate analysis to the subset of buildings with cooling towers and/or evaporative coolers only. This is an important benchmarking decision as the inclusion of air-cooled buildings in regression analysis would dilute the impact of climate on water consumption (as water consumption of air-cooled building HVAC systems is largely independent of climate). The dilution is further exacerbated for the South African data set as the proportion of air-cooled buildings is roughly equivalent to water-cooled buildings (41/84 sample buildings were air cooled); this is in contrast to an Australian data set of which approximately 25% of buildings were air-cooled. The inclusion of air-cooled buildings in climate modelling is one key reason why the US EnergyStar tool makes a much smaller climate correction for water use.

Figure 57 and Figure 58 below demonstrate the differences in observable climate correlations if air-cooled buildings are included in the analysis.

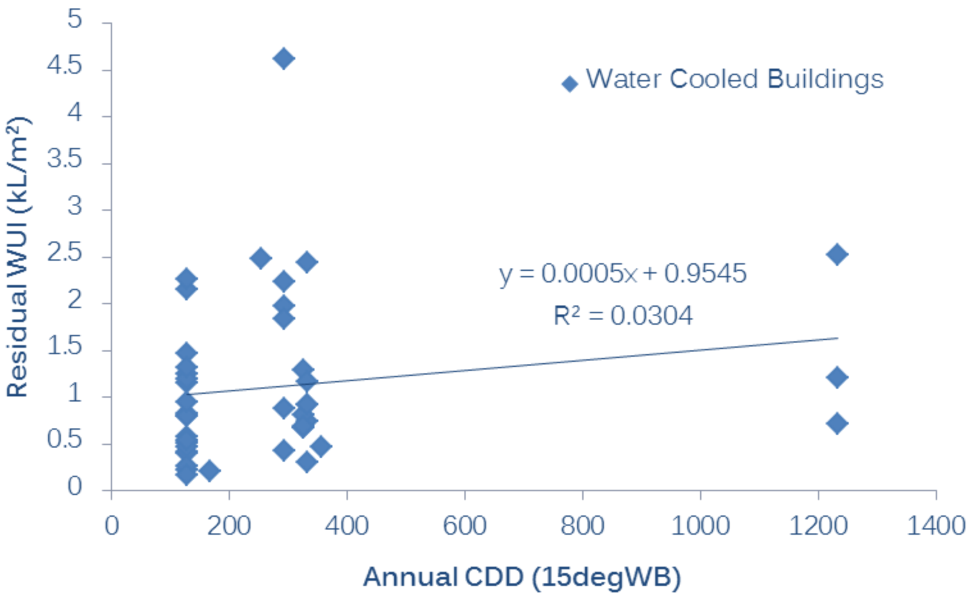


Figure 57: Climate correlation with water-cooled buildings only

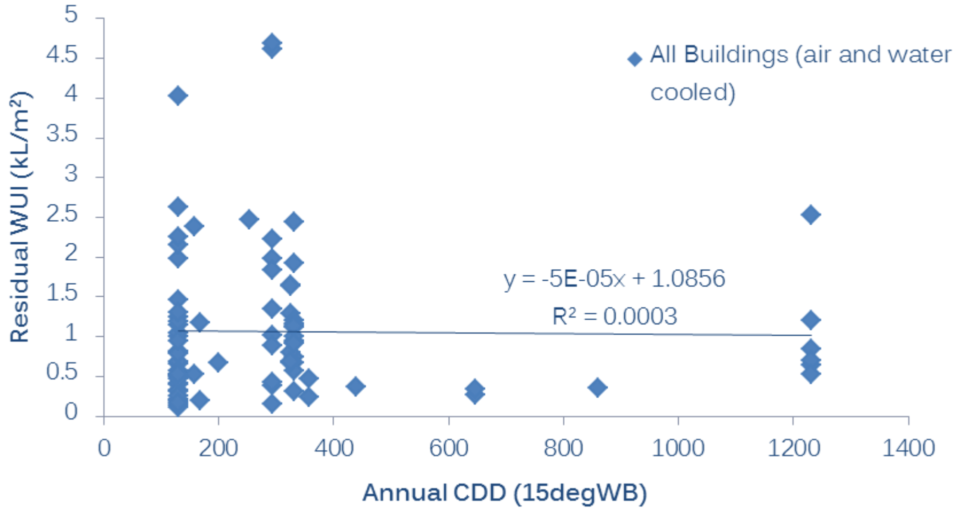


Figure 58: Climate correlation of full sample data (approx. 50% air-cooled buildings)

Figure 58 illustrates that the inclusion of air cooled buildings dilutes any observable climate trends in water consumption. Meanwhile, Figure 57 suggests a climate trend for sample buildings with cooling towers; however, these buildings fall into one of only a few climate zones in South Africa with annual CDD values typically in the range of 230 to 471 degree days per year. Based on the distribution presented, a positive correlation between cooling demand (CDD) and WUI appears to exist. Theory supports this observation in that buildings in cooling dominated climates are expected to consume more water, particularly through HVAC (e.g. cooling towers); however, the severely limited range of variation in CDD means that the statistical confidence of the observed correlation is limited and extra care must be taken in extrapolating the correlation to the broader population (with more diverse climates).

The water cooled building sample climate correlation is re-examined after excluding the three influential sites with over 1,200 annual CDD.

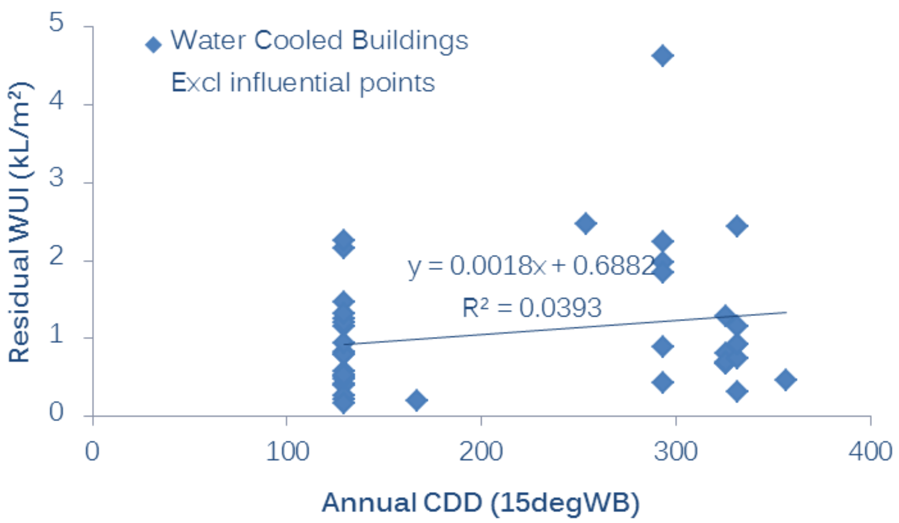


Figure 59: Correlation between annual CDD and residual WUI excluding influential point

There are two observations to be made based on Figure 59:

- The positive trend suggests that an increase in CDD corresponds to an increase in WUI at the rate of approximately 0.0018kL/m^2 per degree day. Mathematically, this relationship implies that an increase in 1 cooling degree day leads to an increase in heat rejection of approx. 40W/m^2 (based on 5 cycles of concentration and 2.4MJ/kg of evaporative losses); this increase in cooling load is inconsistent with theory (over-estimated) and should not be included in the water benchmark. However, if the two influential points are not excluded (e.g. Figure 57), the relevance of the apparent slope is markedly improved (0.0007kL/m^2 per degree day or roughly 16W/m^2 increase in heat rejection).
- There are two cities with similar climates but noticeably different WUI (at least within the subset of water-cooled buildings). This is likely due to external environmental or socio-economic factors (e.g. water efficiency awareness in areas with limited/regulated access to fresh water).

Based on the unreliable nature of the empirical correlations (which is dependent on the inclusion/exclusion of influential points), it is recommended that a theoretical climate correction for water consumption is considered in favour of an empirical approach. The sample data's limited CDD variation implies further uncertainty in any extrapolation and provides additional justification against an empirical correction. We therefore recommend that the water benchmark adopt a climate correction of 0.0009kL/m^2 per CDD (increase in heat rejection of approx. 20W/m^2/CDD) for water-cooled office buildings.

6.2.2 Occupancy hours

Building services operate different hours and days depending on scheduling, leasing requirements and tenant occupancy patterns. In theory, buildings that operate longer hours should consume more water and thus more water per square metre.

As part of the detailed data set, owners/operators were asked to indicate the number of hours per week their buildings were required to operate (e.g. provide air conditioning) for tenants. Of the 84 sites in the detailed subset, all sites were able to provide an indication of their operating hours; the responses are presented in Figure 60 below.

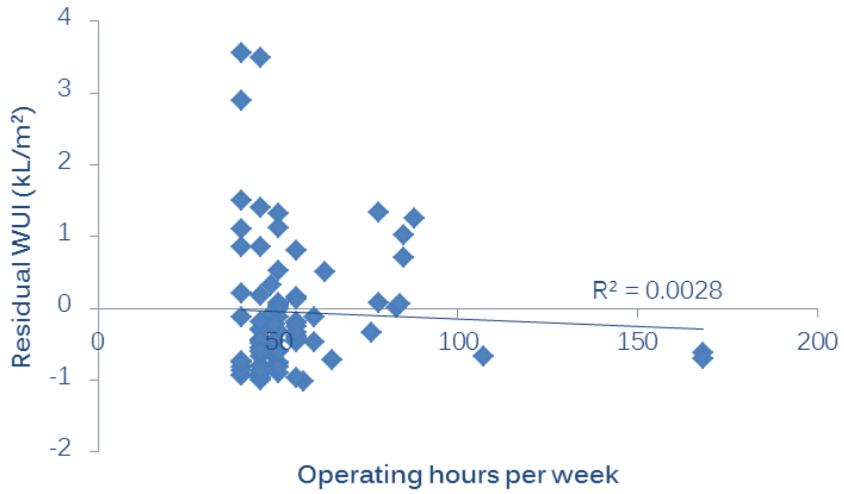


Figure 60: Correlation between building operating hours and residual WUI

Based on the distribution of the residuals, there is no relationship between building operating hours and building performance; this is further exacerbated by the relatively narrow range of observed building hours (between 45 and 65 hours).

While the absence of empirical evidence is in line with the findings of several other benchmarking studies relating to commercial and retail buildings, a theoretical occupancy-hours correction could nevertheless be applied to account for increased water use as a result of longer occupancy. An assumption may be made regarding the expected occupancy-hours (average 45.9 hours/week) and average occupancy during after-hours (e.g. 50%); taking both factors into account, the occupancy correction for water use is:

1 / 45.9 hours × 50% occupancy = **1.1% water consumption per hour of occupancy** (more specifically, deviation from the standard 45.9 hours per week).

6.2.3 Occupant density

The total number of building occupants is a good proxy of how much necessary servicing the building provides and how much water is used (each additional occupant would increase water consumption by an expected margin). Notably, occupant density can be difficult to measure and verify in a rating tool since people are constantly moving and adjusting for part time workers may prove difficult.

Of the 84 sites in the detailed subset, 76 sites were able to provide a count for the number of occupants in the building; the responses are presented in Figure 61 below.

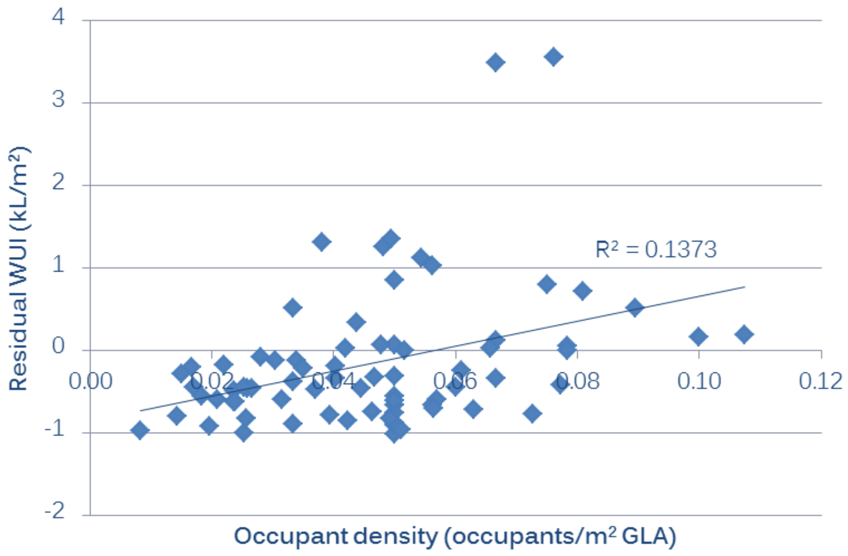


Figure 61: Correlation between occupant density and residual WUI

The residual distribution observed in Figure 61 indicates that there is a strong positive correlation between WUI and occupant density in line with expectations. However, a portion of the correlation is being driven by the two influential points with high WUI (residual WUI > 3 kL/m^2). These sites exert excessive influence and should be excluded from the benchmark development. While it is premature to conclude that occupant density is a significant driver of water consumption, the empirical results justifies further regression analysis.

6.2.4 Computer density

Similar to occupant density, the computer density metric provides an indication of how much building services is required. Whereas computer density was directly related to energy consumption, it is in this instance, a proxy for occupant density which is more directly related to water consumption. Nevertheless, the strength of its correlation to WUI should be examined.

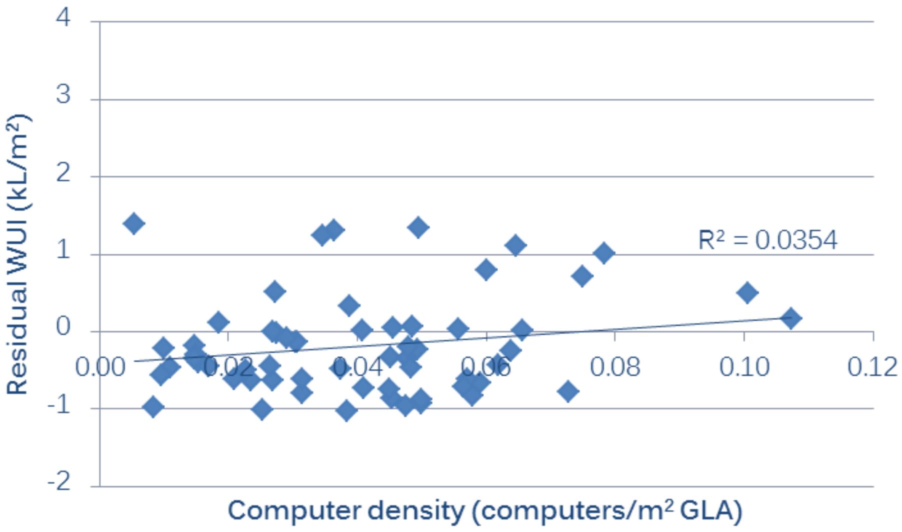


Figure 62: Correlation between computer density and WUI

In comparison to occupant density, Figure 62 shows a much weaker correlation between computer density and WUI. This outcome suggests that computer density is not an ideal correlator for building WUI. Exergy recognises that in the event that occupancy data cannot be reliably collected, computer density may represent the best alternative, however, there is the potential (in certain cases) for computer density to far exceed occupant density, thereby distorting rating outcomes.

6.2.5 Lettable office space (% of GLA)

As the full sample data is mostly limited to GLA, the area data often includes non-office spaces such as retail and common areas (e.g. foyers/lobbies). If there are considerable differences in water use intensity between different space types, there should be a noticeable correlation between % lettable office space and WUI; this is particularly true for many retail tenancies (e.g. cafes and supermarkets) where water consumption far exceeds office tenant water use.

Of the 84 sites in the detailed subset, 68 sites were able to provide the size of the building office space in m^2; the responses are presented in Figure 63 below.

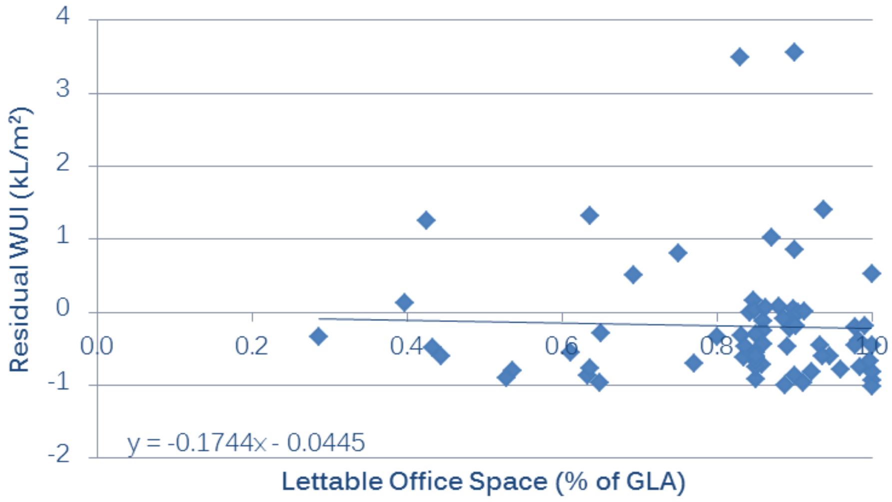


Figure 63: Correlation between Lettable Office Space (% of GLA) and residual WUI

There is slight trend in Figure 63 for the residual WUI when compared against % of Lettable Office Space but this is insufficient evidence to support an empirical correction for the proportion of office space. This outcome suggests that in commercial buildings, the water consumption impact of non-office spaces are not significant enough to correct for explicitly.

6.2.6 Vacancy rate (% of GLA)

A vacancy rate could be incorporated into the model as current total GLA figures are unadjusted for vacancy. While vacant spaces count towards the total GLA of a building, they do not support any occupants and should therefore consume no water. Some international rating tools deal with vacancy by only assessing building areas that are occupied and in regular use; partial areas are assigned where a space is occupied for less than the full calendar year.

Of the 84 sites in the detailed subset, 70 sites were able to provide information on average vacancy rate throughout the year; the responses are presented in Figure 64 below.

Figure 64: Correlation between building vacancy rate and residual WUI

Ideally, vacant and unoccupied spaces do not require normal building services; this should lead to reduced water consumption. To a lesser degree, the reduction in building occupants should also lead to lower water consumption. However, the empirical evidence is unable to support a substantive correlation between vacancy and water usage. This was expected as vacancy does not generally lead to lower HVAC loads in practice due to poor building turn down. The possibility also exists that a number of survey respondents misinterpreted the query and instead specified the occupancy rate; this is a distinct possibility for buildings that are reporting over 50% vacancy. However, a more counterintuitive correlation results in Figure 65 below when potential outliers are excluded (more water usage as vacancy rate rises).

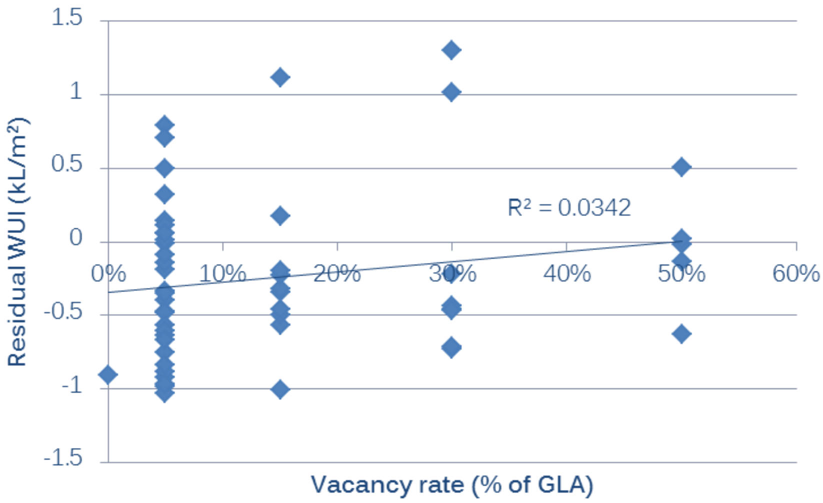


Figure 65: Correlation between building vacancy rate and residual WUI (excluding potential outliers)

While there is insufficient empirical evidence to justify a benchmark correction, from a policy perspective, it is highly recommended that GLA assessments exclude vacant spaces to encourage water savings through building turn down.

6.2.7 Car park density (car parks per m^2 GLA)

Only some buildings provide car parking to its tenants or to the public. Under some other international rating tools, water use of public car parks (i.e. not limited to tenants) is excludable from assessable water consumption; water use of car parks dedicated to tenant use is considered a building service and included in assessable water consumption. It is important in this instance to see if availability of car parks actually results in higher WUI for the South African buildings.

Of the 84 sites in the detailed subset, 69 sites were able to provide information on car park density and whole building water consumption including car park services; the responses are presented in Figure 66 below.

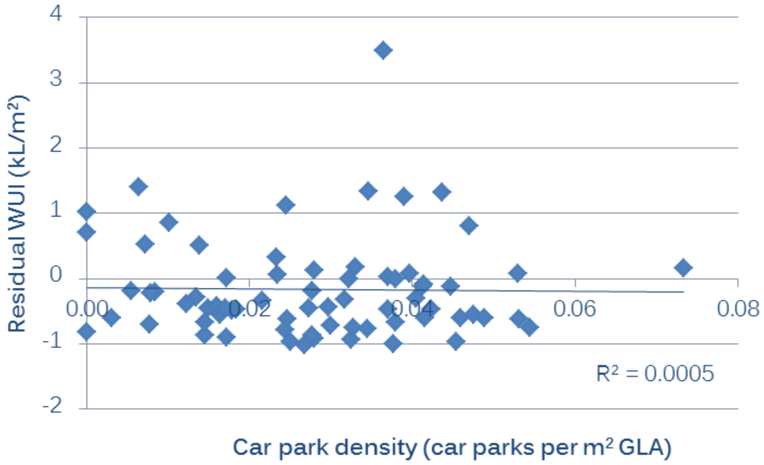


Figure 66: Correlation between car park density and residual WUI

When compared to whole building WUI, the impact of car park water consumption appears to be minimal. Based on the trend above (or lack thereof), there is no empirical evidence to support a residual correction based on car park density.

6.2.8 Irrigation Area (% of GLA)

Some buildings provide irrigation to external land mass or facilities such as gardens and water features. Some international tools exclude these irrigation services where it is deemed to service a function other than the office building, e.g. retail water fountain. Where irrigation occurs within the boundary of a building site and is not dedicated to retail/non-office end users, the irrigation consumption is included in a building's assessable water consumption. This position ensures that buildings actively reduce the size of their irrigation obligations which are not considered essential in these cases. Despite the lack of justification from a policy perspective, it is nevertheless important to gauge the scale of impact irrigation is likely to have on a building's water consumption.

Of the 84 sites in the detailed subset, 61 sites were able to provide information on irrigation area and whole building water consumption; the responses are presented in Figure 67 below.

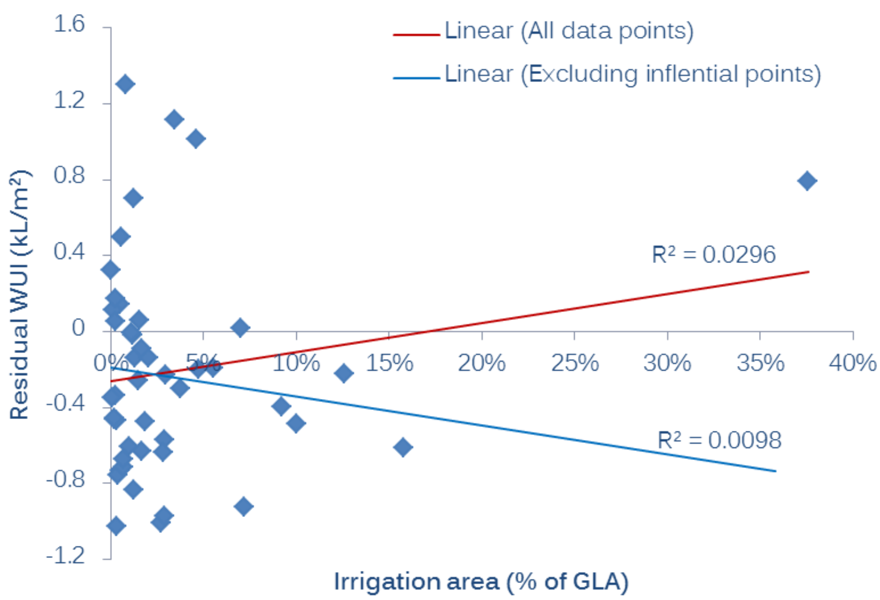


Figure 67: Correlation between irrigation area (% of GLA) and residual WUI

While there appears to be a weak correlation between the size of the irrigation area and WUI, the relationship is entirely driven by the one site with irrigation area size greater than 20% of the GLA. Based on this outcome, there is no empirical justification to include a correction in the water benchmark model for irrigation services. This is in line with previous Exergy investigations which indicate irrigation accounts for only 3-4% of total office building water consumption on average.

6.2.9 Conclusion

This section sought to identify any underlying relationships between building water performance (residual WUI) and a number of potential consumption drivers. Based on observed linear correlations and the strength of such correlations, the most significant driver of building WUI is the occupant density metric. While data on occupant density is available as part of the survey, the quality of the data is questionable and it will be necessary in a formal benchmark tool to devise an appropriate survey methodology. A theoretical climate correction is recommended for the water benchmark as there is too much uncertainty in the observed empirical correlation between climate and water use.

6.3 Water Benchmark Model

From Equation 13, we have

$$Actual\ WUI = Expected\ WUI + \varepsilon$$

Where the Expected WUI is the full sample average WUI, or 1.14 kL/m^2.

Residual analysis carried out in the preceding sections identified that HDD and occupant density may be useful in explaining part of the variability in ε. Linear regression will be utilised in this section to quantify the impact of these factors to construct the final benchmark model.

6.3.1 Linear regression model

The relationship between residual WUI and occupant density may be described by the following simple linear regression model:

$$\varepsilon = \beta_0 + \beta_{occ} \times Occ\ Density + \delta \qquad \textbf{Equation 14}$$

Where β_0 and β_{occ} are the regression coefficients evaluated via least squares linear regression modelling; δ is the residual term that includes the portion of the variation in residual WUI that cannot be explained by occupant density.

Analysing the data via a statistics package provides the following output for Equation 14, note only 66 sites were able to provide reliable occupancy data (excluding 2 outliers discussed in Section 6.2.3 and 8 sites in remote regions which are not representative of the full sample as discussed in Section 5.1):

Regression Statistics	
Mode Significance F	0.00299
R Square	0.130
Observations	66

	Coefficients	*Standard Error*	*P-value*
Intercept	-0.692	0.167	0.000101

Occ density	10.3	3.32	0.00299

Table 19: Regression output for occupant density and HDD corrections

The coefficients in Table 19 quantify the relationship between occupant density and residual WUI, suggesting a benchmark model of the following form:

$$Predicted\ WUI\ =\ 1.14 + (\beta_0 + \beta_{Occ}\ \times\ Occ\ Density\ )$$
$$Predicted\ WUI\ =\ 1.14 + (-0.692\ + 10.3 \times Occ\ Density)$$

Equation 15

Other key indicators in Table 19 provide model diagnostics and statistical support for the significance of the relationship, namely:

- The regression R^2 coefficient of 0.130 indicates that approximately 13% of variation in residual WUI can be explained by occupant density and HDD. Note that a large portion of the variation in water consumption has already been explained by building size (GLA)
- The model significance is acceptable, suggesting that there is better than 99.7% confidence in the significance of the relationship (higher than 99.7% certainty that there exists a relationship between residual WUI and the two factors).
- The p-value for the coefficient β_{Occ} is very low. This is a strong indication of coefficient significance (i.e. there is more than 99% confidence that occupant density coefficient is non-zero).

6.3.2 Adjusting the Model for Occupancy Hours

To include the theoretical occupancy hours correction described in Section 6.2.2, the benchmark predicted WUI in Equation 15 can be adjusted by 1.1% for each hour above or below the standard occupancy of 45.9 hours per week. Note that the correction assumes after hours occupancy of 50% and that after hours loads are the same as daytime loads. The new equation becomes:

$$\boldsymbol{Predicted\ WUI}\ = (\mathbf{0.448} + \mathbf{10.3} \times \boldsymbol{Occ\ Density}) \times [\mathbf{1} + \mathbf{0.011} \times (\boldsymbol{Occupancy\ Hours} - \mathbf{45.9})]$$

Equation 16

6.3.3 Adjusting the Model for Climate

As previously determined in Section 6.2.1, a purely theoretical approach may be taken in correcting water consumption for climate effects. However, this is complicated by the fact that there are two distinct groups of buildings, being air cooled and water cooled, where the latter's water consumption is much more climate dependent. One could incorporate a tapered climate correction as the building rating increases, thereby requiring the most efficient buildings to be rated independently of climate (no climate correction), but this is probably not appropriate in this case. Given that the South African rating tool will feature a 0 net consumption rating (with a rating score of 10), there is the option for GBCSA to adopt an earlier cut-off for climate correction.

It is recommended that the South African tool adopts the climate correction for cooling tower consumption of 0.0009kL/m^2 per annual CDD (evaluated with base temperature of wet bulb 15˚C). To ensure standardisation of climate metrics with the energy benchmark model, the correction has been translated to utilise average annual wet bulb temperatures. The median (predicted) water consumption for a given site is therefore:

$$\boldsymbol{Predicted\ WUI} = (\mathbf{0.448} + \mathbf{9.92} \times \boldsymbol{Occ\ Density}) \times [\mathbf{1} + \mathbf{0.011} \times (\boldsymbol{Occupancy\ Hours} - \mathbf{45.9})] + (\mathbf{0.109} \times \boldsymbol{Annual\ T_{avg\_WB}} - \mathbf{1.43})$$

Equation 17

Where ***Annual T$_{avg_WB}$*** is the respective climate zones' annual average wet bulb temperatures in ˚C (by postcode lookup). The strong correlation between average wet bulb temperature and the water climate correction for a range of climates is shown below in Figure 68.

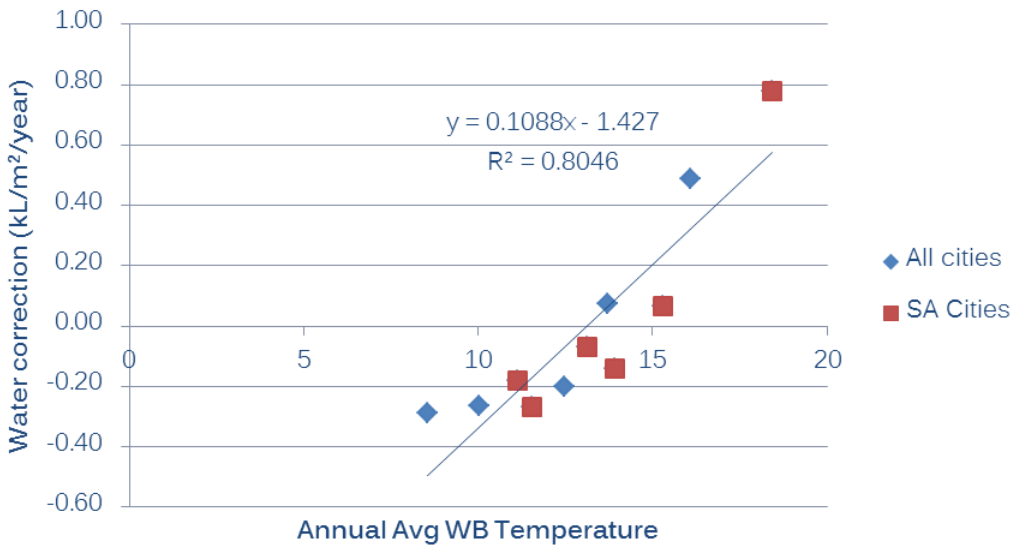


Figure 68: Correlation between annual average wet bulb temperature and water correction

6.3.4 Converting to Predicted Median Consumption

Equation 17 can be used to estimate the market average water consumption of an office building with a specified occupant density by multiplying through with building size (GLA).

$$\boldsymbol{Predicted\ kL} = \{(\mathbf{0.448} + \mathbf{10.3} \times \boldsymbol{Occ\ Density}) \times [\mathbf{1} + \mathbf{0.011} \times (\boldsymbol{Occupancy\ Hours} - \mathbf{45.9})] + (\mathbf{0.109} \times \boldsymbol{Annual\ T_{avg_{WB}}} - \mathbf{1.43})\} \times \boldsymbol{GLA}$$

Equation 18

Before utilising the benchmark model as part of a water rating tool, it is necessary to adjust the model predicted kWh from an estimated average to an estimated median. The use of medians is essential in the context of a rating tool based on relative building performances, as averages may be substantially skewed by outliers and extreme values. Since the distribution of office building WUI is positively skewed (as there is often no upper limit for how inefficient a building can be, see Figure 11), the median building WUI is a more accurate representation for the "middle" efficiency level.

To convert predicted average consumption to predicted median consumption, the predicted consumption in Equation 16 needs to be adjusted by the median residual value of -14.6%. Namely,

$$\boldsymbol{Predicted\ kL} = \{(\mathbf{0.448} + \mathbf{10.3} \times \boldsymbol{Occ\ Density}) \times [\mathbf{1} + \mathbf{0.011} \times (\boldsymbol{Occupancy\ Hours} - \mathbf{45.9})] + (\mathbf{0.109} \times \boldsymbol{Annual\ T_{avgWB}} - \mathbf{1.43})\} \times \boldsymbol{GLA} \times \mathbf{0.892}$$

Equation 19

6.3.5 Final Water Model

As per Equation 19, Figure 69 below compares reported actual water consumption against the Equation 19 benchmark predicted kL water consumption.

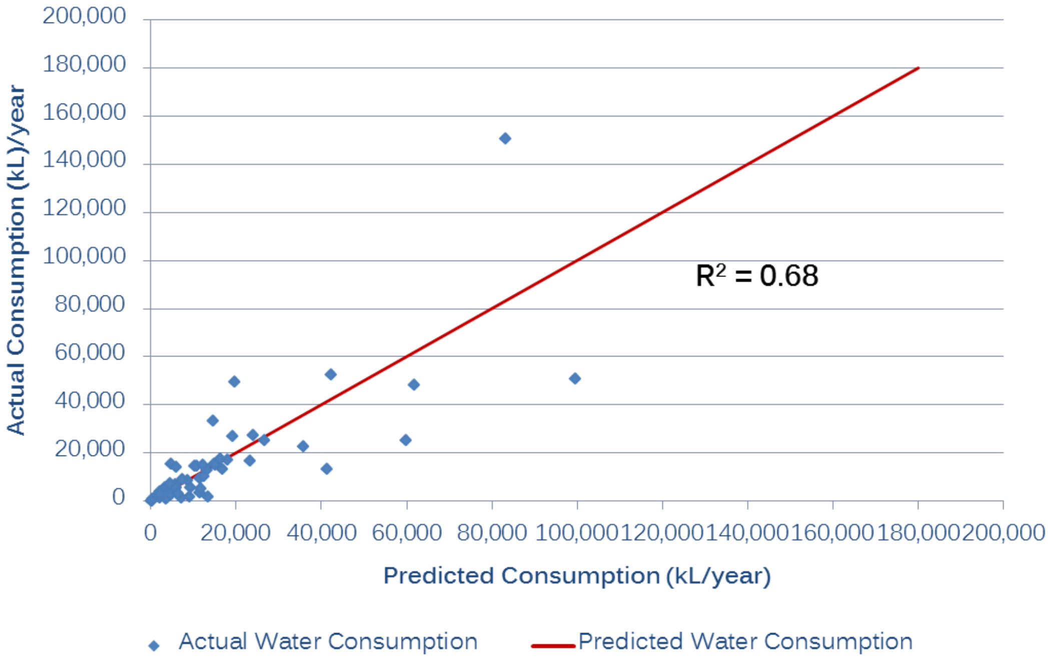


Figure 69: Water benchmark model predicted kL vs. actual kL (excluding potential outlier)

The model fit is generally good with a relatively high R^2 correlation coefficient (0.68) and good spread of data either side of the predicted (median consumption) line. The noisy distribution of the water data contributes to the lower R^2 when compared to the energy benchmark.

6.4 Residual Analysis – Water Benchmark

As per the energy benchmark model, it is necessary to conduct further analysis of model residual to determine whether any inherent biases exist in the model output.

Residual analysis through graphical and regression analysis was conducted for a number of key parameters to examine whether there are any underlying bias issues. Table 13 below presents a summary for both the correlation coefficient (R^2) and statistical significance (p-value) evaluated for each factor's correlation against model % residuals. Strong correlation is usually signified by R^2 in excess of 0.1 (at least 10% of variation in % residuals could be explained by the factor) and high statistical significance is usually signified by p-values less than 0.05 (95% confidence that a non-zero correlation exists).

Factor	R^2	p-value
Fitted values (kL consumption)	0.030	0.18
Building Size (m^2 GLA)	0.013	0.38
Computer Density (computers/m^2)	0.0027	0.71
Occupant Density (occupants/m^2)	0.0039	0.63
Occupancy-Hours (hours/week)[2]	0.05	0.08
Climate (average annual WB ˚C)	0.0088	0.47
% Active Cooling	0.014	0.36
Irrigation Area (% of GLA)	0.029	0.26

Table 20: Residual analysis summary for water model % residual output

As the table demonstrates, in all cases tested, the statistical significance of the correlation with the model % residual was markedly lower than the nominated significance thresholds (except for occupancy hours which is explained in the footnote). On this basis, it is reasonable to conclude that the water benchmark model does not suffer from any underlying bias.

The graphical plots of % residual values against each factor above can be found in Appendix B.

6.5 Recommended Rating Bands

The water benchmark provides a predicted level of water consumption for a whole office building based upon reported characteristics data. The water rating of an individual office building is determined by the difference between the building's actual water consumption and the model predicted median water consumption level. The percentage residuals of the model ρ are calculated as:

$$\rho = \frac{W_{measured} - W_{median}}{W_{median}} \qquad \textbf{Equation 20}$$

Where $W_{measured}$ is the measured water consumption for the whole building and W_{median} is the benchmark predicted (median) water consumption for the building, both expressed in kL per annum. This represents how far the rated building is from the industry median (the middle of the pack).

The distribution of the residuals ρ is shown in Figure 70 below.

[2] Note that the occupancy-hours correlation to % residuals reduces to R^2 and p-value of 0.00036 and 0.89 respectively when we exclude 3 potential outliers reporting longer than 100 hours of operation.

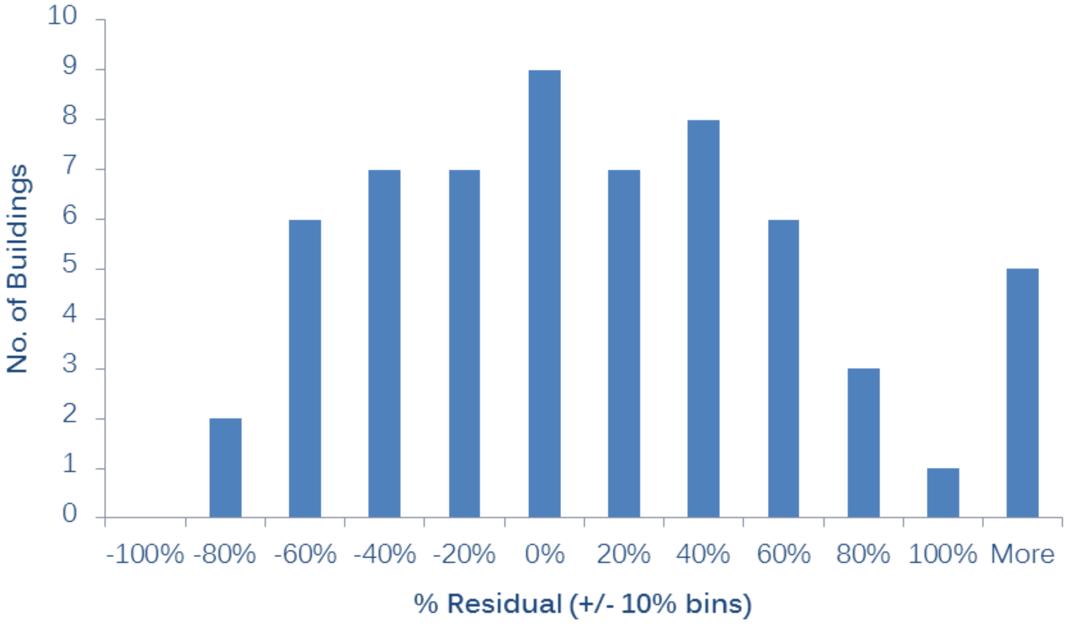


Figure 70: Distribution of water benchmark model residuals (±10% on each bin)

To convert this model into a performance rating tool the following approach has been used to set the rating bands:

- The site's predicted water consumption W_{median} is calculated (Equation 19)
- The site's measured water consumption $W_{measured}$ is obtained (e.g. from utility bills)
- The residual ρ is calculated as described in Equation 20.
- The rating is calculated based on the size of the residual relative to the predicted consumption (percentage residual). The rating equation is based on $R = A - B\rho$ where R is the rating for the building, A is the midpoint of the "median" building's rating band, ρ is the percentage residual and B is the rating band co-efficient.
- The rating value R is rounded down to the nearest integer rating category;
- The highest rating score is 10;
- The lowest rating score is 1 (below this the site is unrateable);

The rating band co-efficient was set on the basis of getting a "desirable" distribution of results. This was done in such a way that the final distribution has not many ratings either: below a score of 1 to make most of the office building population rateable; or, above a score of 7 to set the higher ratings (8, 9 and 10) as aspirational targets for new buildings or refurbishment of existing buildings. This was done in such a way that the final rating distribution has the following characteristics:

- The "median" building performance, represented by coefficient A has been defined at the score of 5.5 to maintain consistency with the energy benchmark.
- The distribution of ratings is suitable (i.e. not biased towards higher or lower ratings).
- Rating score of10 is water neutral (0 net water intake)
- Linear rating scale between scores of 1 and 10 (e.g. absolute difference in kL between scores of 2 and 3 the same as difference between 7 and 8).

On this basis, the rating equation is:

Equation 21

$$R = 5.5 - 4.5\rho$$

The final rating distribution for the sites used in developing the model is shown in Figure 71.

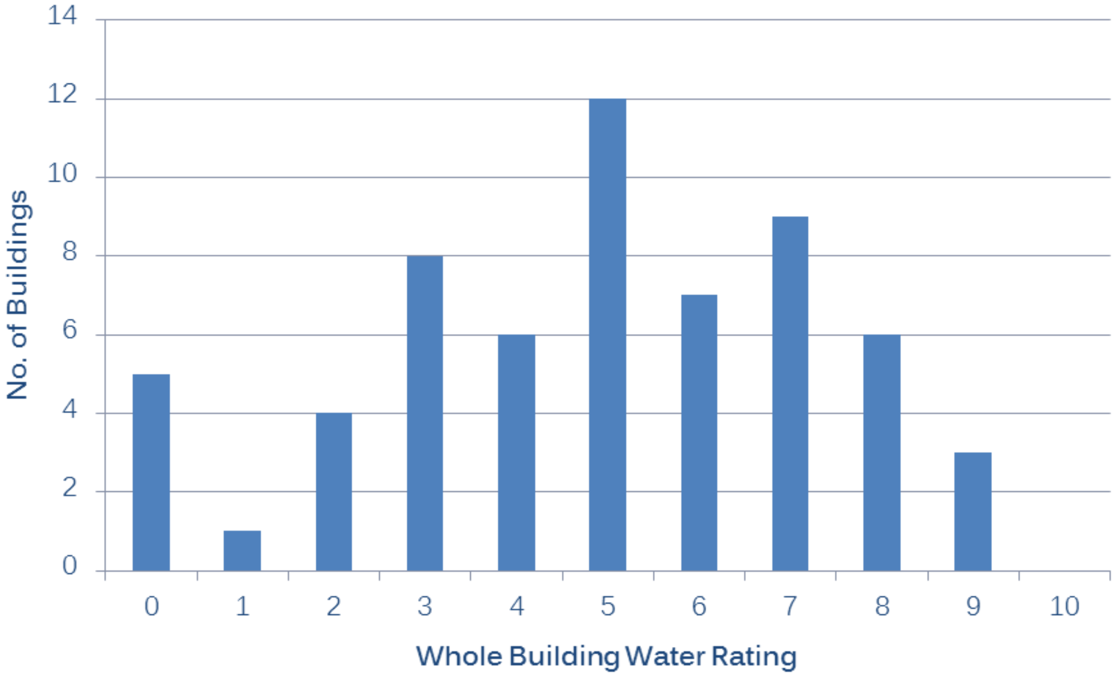


Figure 71: Water benchmark sample buildings' rating distribution

This distribution shows that the rating band coefficients achieve the two objectives of the rating design, being (1) to ensure that most of the building population is rateable and differentiable; and (2) to set an aspirational performance target for new and existing buildings. Note that a rating of 0 in the figure represents an unrateable building (lower score than 1); 6 buildings fall into this category, which is approximately 9% of the sample buildings rated.

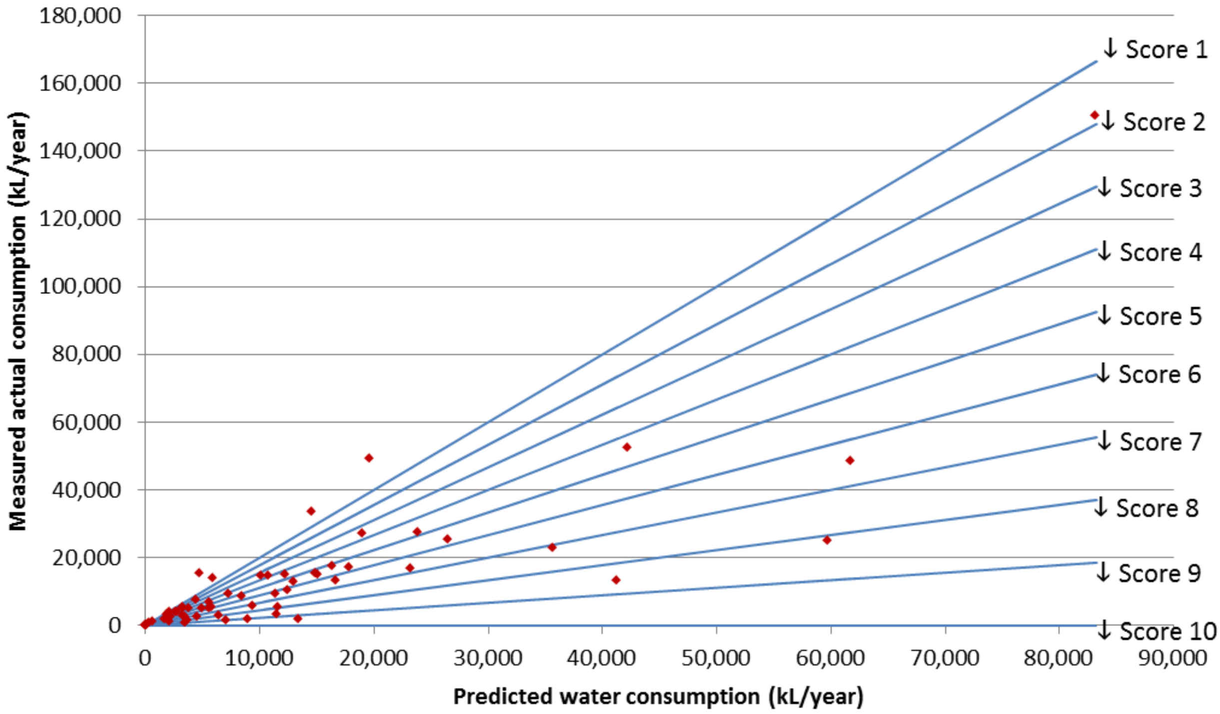


Figure 72: Water benchmark consumption rating bands

The rating bands are a function of all the parameters within the office building – in plain terms, a customised set of rating bands is created for each building, based upon its area, occupant density, occupancy hours and climate.

Rating bands are representative of constant increments in consumption; i.e. the quantity of water (kL) separating a rating score of 1 and 2 is the same as that separating a rating score of 7 and 8. Each rating band is equivalent to approximately 22% of predicted median water consumption (kL). The rating bands are detailed in Table 21 below.

Water rating score, at beginning of rating band	Water consumption compared to benchmark predicted consumption
10	0%
9	22%
8	44%
7	67%
6	89%
5	111%
4	133%
3	156%
2	178%
1	200%

Table 21: Rating bands relative to the regression (average) equation

Note that the middle of the 5th rating band (rating score of 5.5) is set to 100% of the predicted water consumption (building is performing exactly at industry median efficiency level).

7 Acknowledgements

The GBCSA energy and water benchmarking tool was developed using data and feedback from a number of industry stakeholders and their representatives. We would like to acknowledge valuable contributions from:

BUILDINGS DATA PROVIDERS

- Atterbury
- ERIS Property Group
- ESKOM
- Growthpoint
- IDC
- NEDBANK
- Old Mutual

- Sanlam Life, Data provided by JHI
- Standard Bank
- Telkom, Data provided by TFMC
- Vodacom
- Vukile Property Fund Limited, Data provided by JHI and Broll Property Group
- Zenprop Property HoldingsAtterbury
- ERIS Property Group
- Eskom
- Growthpoint
- IDC
- NEDBANK
- Old Mutual
- Sanlam Life, Data provided by JHI
- Standard Bank
- Telkom, Data provided by TFMC
- Vodacom
- Vukile Property Fund Limited, Data provided by JHI and Broll Property Group
- Zenprop Property Holdings

TECHNICAL ADVISORY PANEL

Howard Harris	SP Energy
Rodney Milford	cidb
Lisa Reynolds	Saint Gobain
Chris Davey	Old Mutual
Essop Basha	Growthpoint
Theuns Eksteen	JHI
Eric Noir	WSP
Jeremy Gibberd	Gauge & CSIR
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Samuel Dlamini	Department of Energy
Barry Bredenkamp	NEEA/SANEDI
Stan Garren	IPD
Mark Schneider	IPD

Jess Cleland	IPD

INDEPENDENT PEER REVIEW

ICF International	Energy Star Developer, USA

PROJECT TEAM

Manfred Braune	GBCSA
Martin Smith	Aurecon South Africa
Yovka Raytcheva-Schaap	Aurecon South Africa
Ashley Underwood	Aurecon South Africa
Melany Stevenson	Aurecon South Africa
Dr Paul Bannister	Exergy Australia
Haibo Chen	Exergy Australia

8 References

Choudhary. R, 2011, *A Probabilistic Model for Assessing Energy Consumption of the Non-domestic Building Stock*, Conference Paper, Building Simulation Conference 2011 Australia.

9 Appendix A – Energy Benchmark Residual Analysis

9.1 Residuals vs. Fitted Values

Figure 73 below indicates that the residual distribution is generally unbiased with each prediction. With the exception of a few sites, a large majority of the sites fall within the ±60% residual range. Using a median correction has led to a uniform distribution of positive and negative residuals which is essential to fair rating bands.

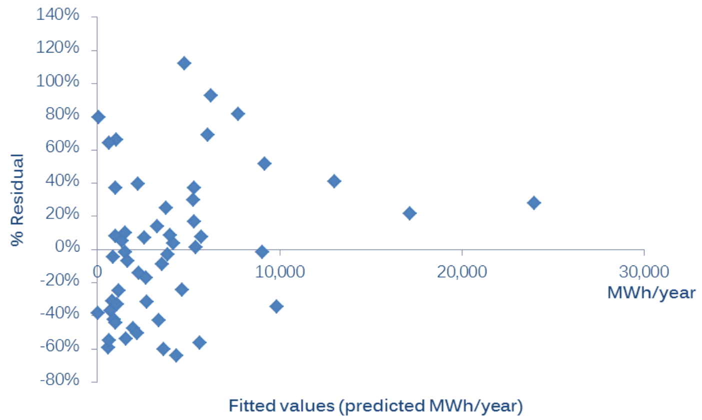

Figure 73: Residual distribution by fitted values

9.2 Residuals vs. Building Size (GLA)

The US Energy Star model corrects whole building EUI for building size, thereby implying that larger buildings are inherently more energy intensive than smaller buildings. It is therefore important for the South African benchmark model to investigate whether empirical data support a building size correction for EUI.

Figure 74 compares benchmark % residuals against building size below.

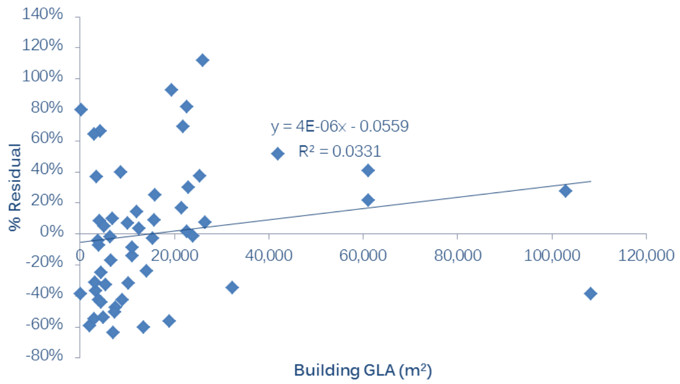

Figure 74: Energy benchmark model % residual distribution by building size (GLA)

The low R^2 value in the plot above suggests that the relationship between building size (GLA) and model % residual is not statistically significant (only 3% of variation in % residual is explained by building size). Further linear regression analysis confirmed this observation.

9.3 Residuals vs. Computer Density

There is strong confidence that the correction for computer density is appropriately weighted as it was evaluated using least squares regression. This is further demonstrated by Figure 75 which shows no computer density bias in the model % residual distribution.

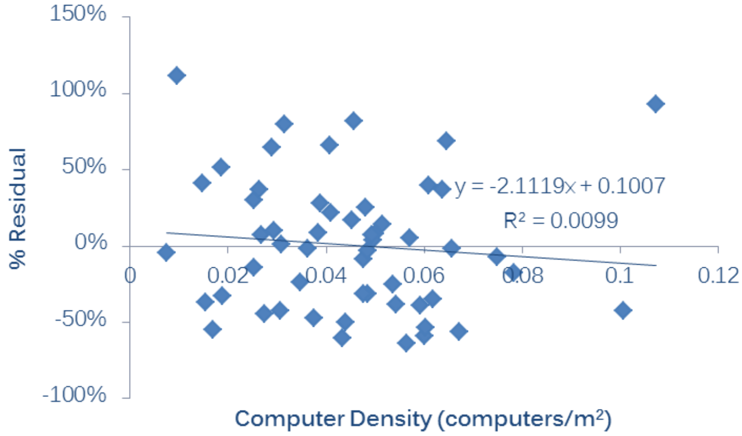

Figure 75: Energy benchmark model % residual distribution by computer density

9.4 Residuals vs. Occupant Density

As occupant density and computer density are strong correlated, it is therefore expected that similar to computer density, no bias would be observed for occupant density. This is confirmed by Figure 76 below.

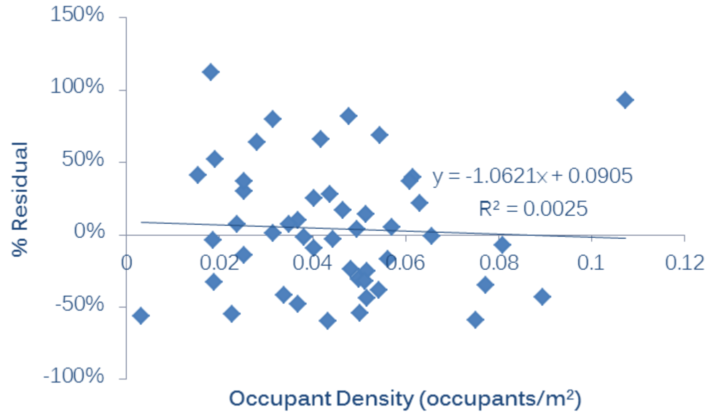

Figure 76: Energy benchmark model % residual distribution by occupant density

9.5 Residuals vs. Occupancy-hours

There are concerns that the scale of the theoretical occupancy-hours correction developed in Section 4.3 is excessive and could potentially distort the fairness of rating outcomes. This is examined in Figure 77 below which compares the model % residuals to occupancy-hours. Note that the two potential outliers with operating hours over 100 hours per week have been excluded from this analysis.

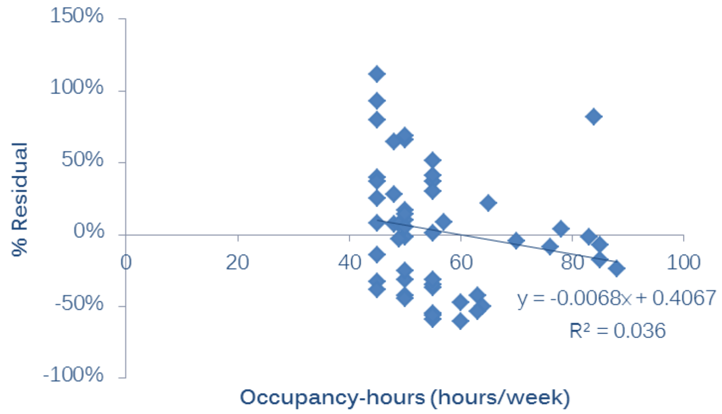

Figure 77: Energy benchmark model % residual distribution by occupancy-hours

The plot above shows very limited variation in % residual by operating hours and in general there is insufficient statistical evidence to suggest that an occupancy-hours model bias exists.

9.6 Residuals vs. Climate

The theoretical climate correction developed through simulation is tested in Figure 78 below for bias. Although there is a very weak trend towards buildings with longer operating hours receiving slightly better ratings, this correlation is not statistically significant given the very weak R^2 value.

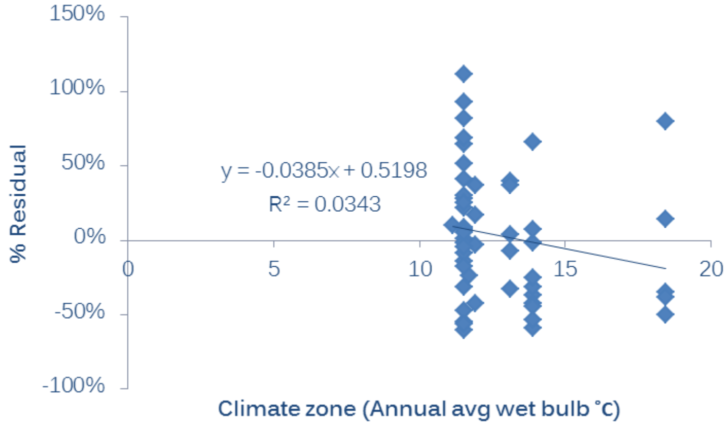

Figure 78: Energy benchmark model % residual distribution by climate zone (annual average wet bulb ˚C)

9.7 % Active Cooling

The US EnergyStar benchmarking tool corrects for the proportion of building cooled by the HVAC system. For the sample of whole building data from South Africa, there is no empirical basis for such a correction. Figure 79 below provides further support against a benchmark correction.

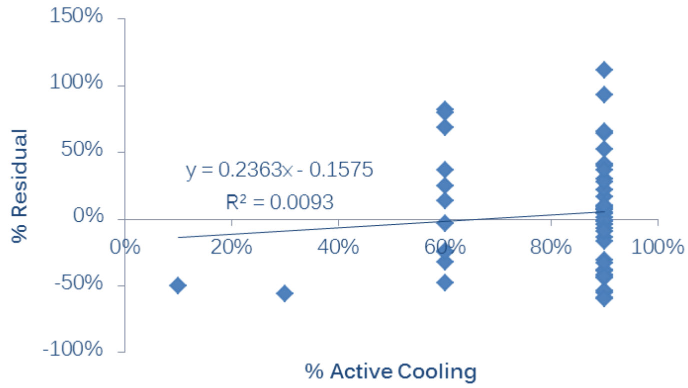

Figure 79: Energy benchmark model % residual distribution by climate zone (annual average wet bulb ˚C)

10 Appendix B – Water Benchmark Residual Analysis

10.1 Residuals vs. Fitted Values

Figure 80 below indicates that the residual distribution is generally unbiased with each prediction. With the exception of a few sites, a large majority of the sites fall within the ±60% residual range. Using a median correction has led to a uniform distribution of positive and negative residuals which is essential to fair rating bands.

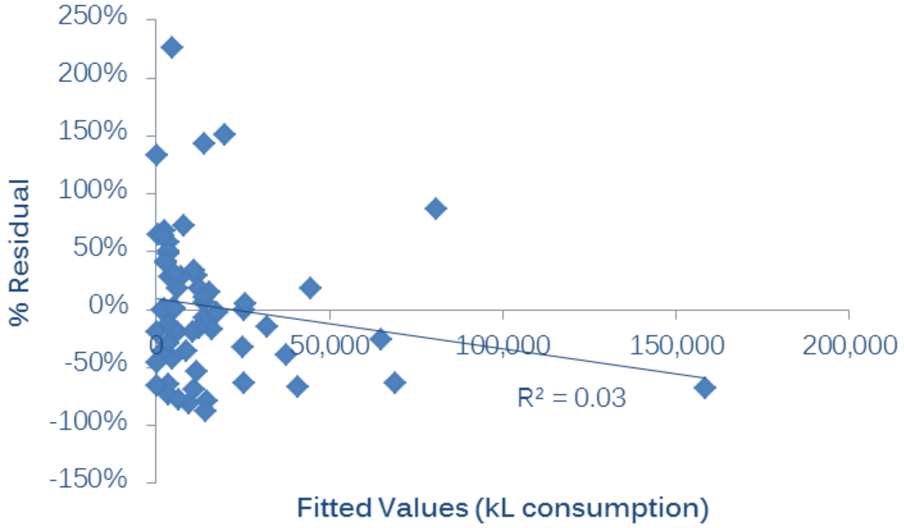

Figure 80: Water benchmark model % residuals distributed by fitted values

10.2 Residuals vs. Building Size (GLA)

There is little evidence to suggest a further building size correction for WUI. The low R^2 value in the plot below suggests that the relationship between building size (GLA) and model % residual is negligible (only 1% of variation in % residual can be explained by building size).

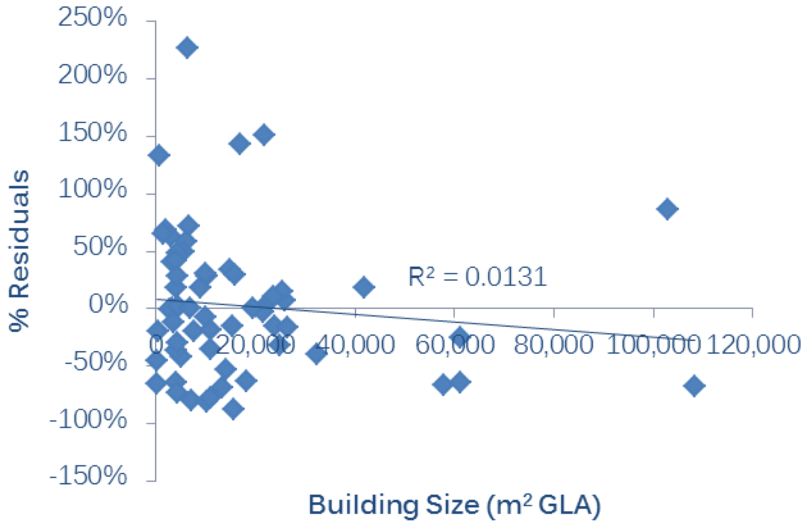

Figure 81: Water benchmark model % residuals distributed by building size (GLA)

10.3 Residuals vs. Computer Density

Given the strong cross-correlation to occupant density (which is corrected for in the benchmark model for water), it is unlikely that there would be residual correlation between computer density (or occupant density) and % residuals. This is demonstrated below.

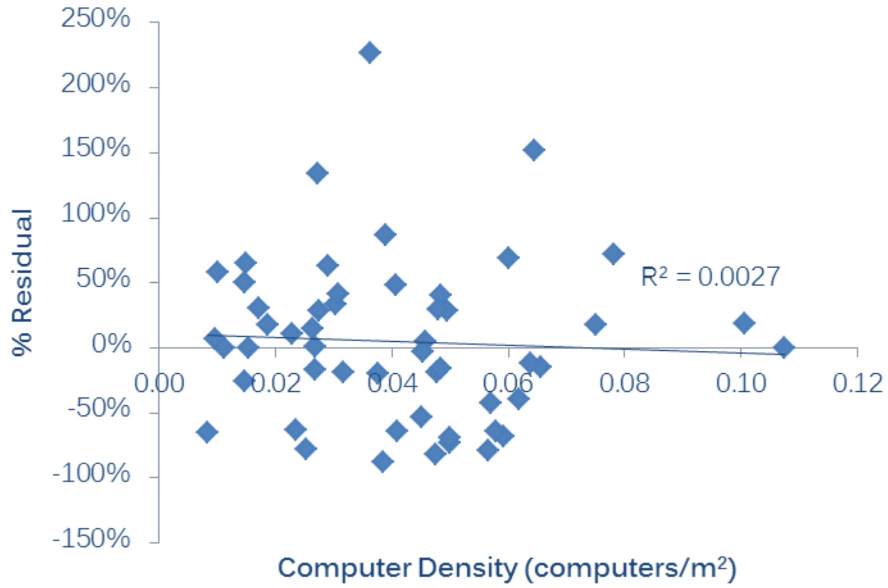

Figure 82: Water benchmark model % residuals distributed by computer density (computers/m^2 GLA)

10.4 Residuals vs. Occupant Density

Similar to the computer density comparison, there is no indication of model bias with occupant density.

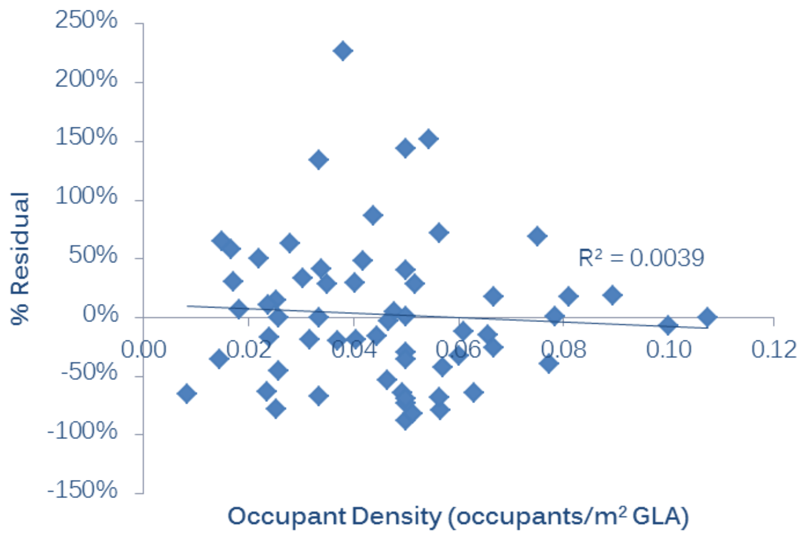

Figure 83: Water benchmark model % residuals distributed by occupant density (computers/m^2 GLA)

10.5 Residuals vs. Occupancy-hours

There are concerns that the scale of the theoretical occupancy-hours correction developed for the water benchmark is excessive and could potentially distort the fairness of rating outcomes. This is examined in Figure 84 below which compares the model % residuals to occupancy-hours. Note that the two potential outliers with operating hours over 100 hours per week have been excluded from this analysis. The graph shows that there appears to be some slight bias though the statistical significance of the correlation is relatively weak (p-value = 0.11).

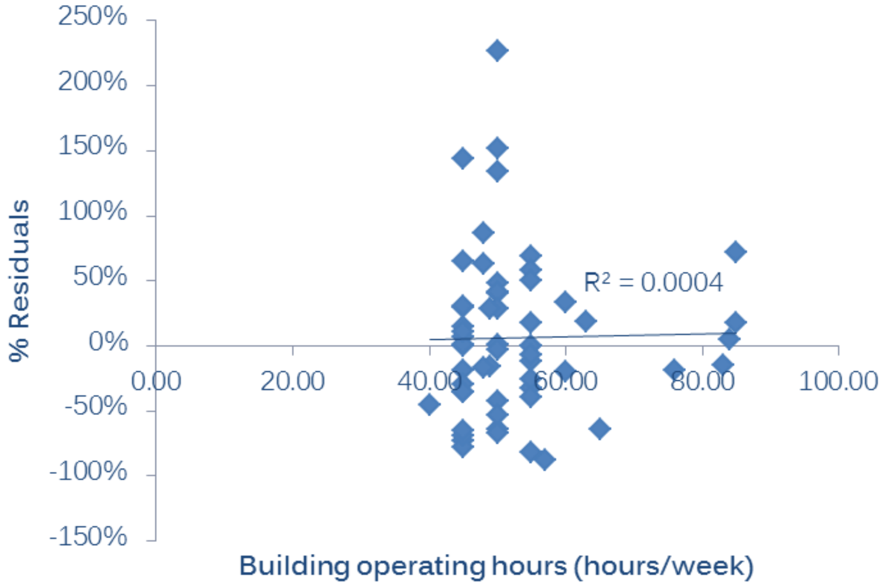

Figure 84: Water benchmark model % residuals distributed by building operating hours

10.6 Residuals vs. Climate

Figure 85 below demonstrates that climate has not been over-corrected in the water benchmark. The residuals have been plotted against CDD (not average WB temperature) to verify that the translation from a CDD based correction to a WB temperature based correction has not introduced any bias into the model.

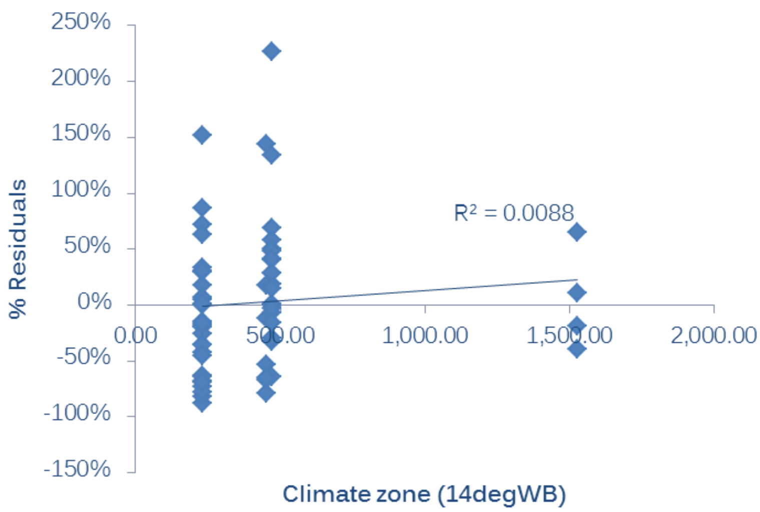

Figure 85: Water benchmark model % residuals distributed by climate (14degWB)

10.7 Residuals vs. % Active Cooling

Figure 86 below shows no bias in the benchmark output with % active cooling provided by the building.

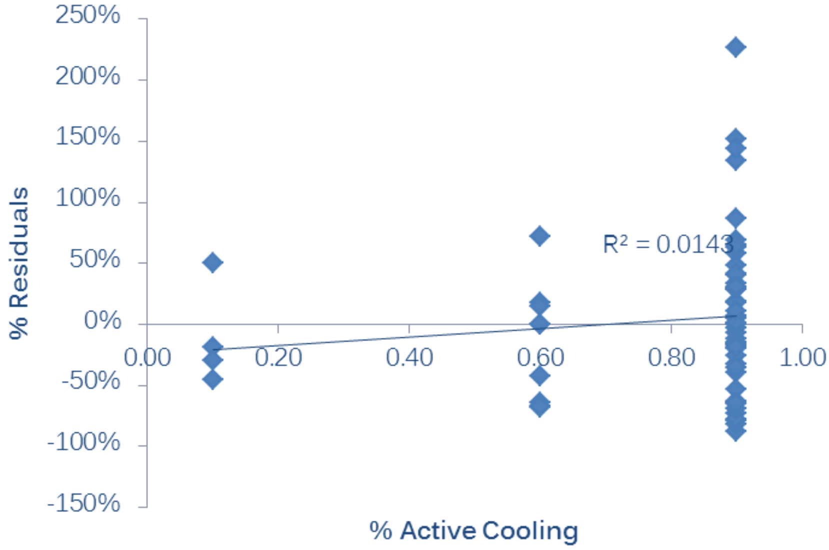

Figure 86: Water benchmark model % residuals distributed by % Active Cooling

10.8 Residuals vs. Irrigation (% of GLA)

The data received with respect to irrigation is very noisy and the observed empirical correlation is dominated by individual influential points which reduce correlation relevance and reliability. More accurate data on irrigation over a broader range of irrigation areas will be required before a more meaningful conclusion can be drawn.

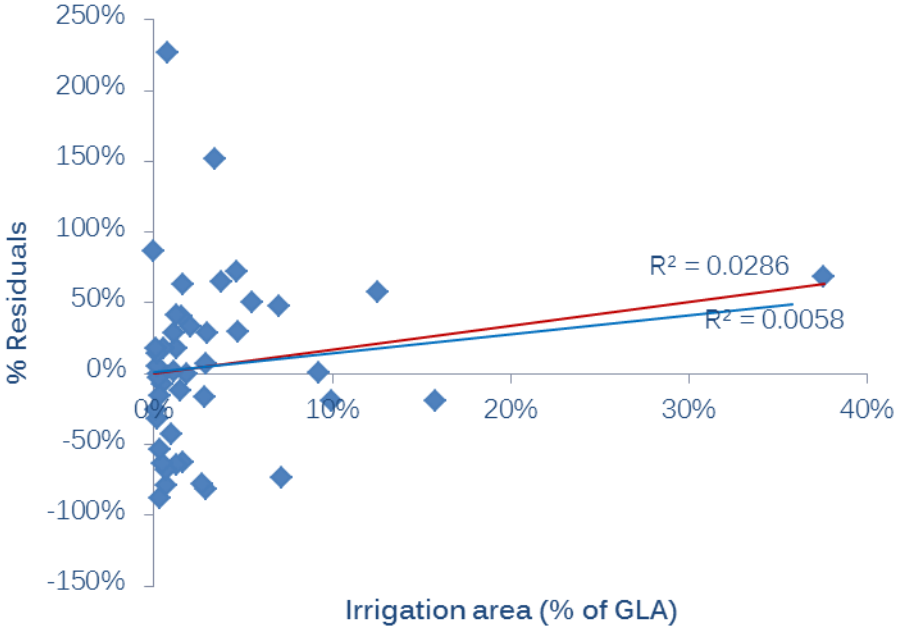

Figure 87: Water benchmark model % residuals distributed by irrigation area (% of GLA)